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Landscape structure and land use affects estuarine benthic invertebrates in the Virginian Biogeographic Province, USA.

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Abstract

Estuaries are dynamic transition zones linking freshwater and oceanic habitats. These productive ecosystems are threatened by a variety of stressors including human modification of coastal watersheds. In this study we examined potential linkages between estuarine condition and the watershed using multimodel inference. We examined attributes at the watershed scale as well as those associated with riparian areas but found that they were highly correlated. We also examined whether attributes closer to the estuary were more strongly related to benthic invertebrate condition and found that this was not generally true. In contrast, variability within the estuary strongly impacted model results and suggests that future modeling should incorporate estuarine variability or focus on the individual stations within the estuary. Modeling estuarine condition indicated that inherent landscape structure (e.g., estuarine area, watershed area, watershed:estuary ratio) is important to predicting benthic invertebrate condition and needs to be considered in the context of watershed/ estuary planning and restoration.

Keywords

watershed; estuary; invertebrates

Introduction:

Estuaries are dynamic transition zones linking freshwater and oceanic habitats. These aquatic systems are some of the most productive ecosystems in the world due in part to the mix of habitats in these areas as well as delivery of freshwater (Lerberg et al. 2000), sediment (Thrush et al. 2004), organic matter (Sakamaki et al. 2010) and nutrients (Dauer et al. 2000, Paerl et al. 2003) from the surrounding watershed. While healthy estuaries rely on freshwater, sediment, carbon and nutrient inputs, human modification of the watershed has greatly increased (or in some cases, decreased) these inputs causing adverse impacts such as sediment contamination (Comeleo et al. 1996, Paul et al. 2002), salt marsh loss (Day et al.

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2000), sediment smothering (Thrush et al. 2004) and eutrophication (Dauer et al. 2000, Paerl et al. 2003).

Since management actions commonly center on land and water management in the watershed, it is important to be able to understand the linkages between estuarine condition and the watershed. Several studies have shown that watersheds can impact estuary condition. Paul et al. (2002) showed linkages between sediment contamination and watershed land use, although the best models also included estuarine hydrology and sediment grain size or organic carbon. King et al. (2004) showed a significant relationship between white perch PCB levels and watershed land use, especially to lands closer to the estuary. Comeleo et al. (1996) had also shown that sediment contamination was more strongly related to land use closer to the estuary. Edgar and Barrett (2000) showed that benthic invertebrates were sensitive to population density within the watershed. Holland et al. (2004) showed that, analogous to freshwater studies, as population density increased, impervious cover increased. As impervious cover increased, tidal creek sediment contamination and stress tolerant taxa increased while stress sensitive taxa decreased. Dauer et al. (2000) showed a more nuanced pattern. Although good benthic condition was positively correlated with forested land cover, benthic invertebrates were primarily affected by land use indirectly. For example, invertebrate condition was negatively correlated with low dissolved oxygen condition, which in turn was positively correlated with population density and percent urban land. Hale et al. (2004) found significant relationships between land use, especially in riparian zones, and benthic fish and invertebrates. Bilkovic et al. (2006) showed that benthic invertebrate condition was highest in estuaries with forested watersheds and lowest in those with more developed watersheds.

Macroinvertebrates have commonly been used to assess condition in estuaries (Pinto et al. 2009, Dauvin et al. 2010). They are abundant and diverse, representing many different phyla (Snelgrove 1998) utilizing multiple habitats and feeding strategies (Rhoads 1974, Weisberg et al. 1997, Little 2000). Macroinvertebrate assemblages also respond predictably to pollution (Pearson and Rosenberg 1978), are relatively sedentary, and act as integrators of stress over months to years (Weisberg et al. 1997, Paul et al. 2001). These assemblages have commonly been assessed using benthic indices that summarize aspects of the invertebrate community into a single number that can be used by environmental managers (Engle and Summers 1999, Pinto et al. 2009). For this study we used two benthic indices - the Virginian Province benthic index (VP BI; Paul et al. 2001) which was used by the U.S. EPA to assess estuarine condition from 1990 to 2010 and U.S. M-AMBI (Pelletier et al. 2018) which was used to assess estuarine condition for the U.S. EPA's National Coastal Condition Assessment from 2015 onward. For both indices, we examined the mean estuary index value, as well as accounting for variation within the estuary.

We also wanted to determine if the spatial arrangement of watershed variables was important in predicting benthic invertebrate condition. Spatial arrangement has been shown to be important when relating watershed attributes to aquatic condition (Comeleo et al. 1996, King et al. 2004, Hale et al. 2004). Sponseller et al. (2001) and Hale et al. (2004) showed the importance of riparian land use to aquatic communities. The importance of riparian buffers to water quality is well documented (Mayer et al. 2007). Naturally vegetated riparian buffers

can reduce the amount of water, sediments and nutrients that enter streams (Weller et al. 1998) and later enter estuaries. In this study, we examined variables at the watershed scale as well as those associated with riparian areas. We also examined whether variables closer to the estuary were more strongly related to benthic invertebrate condition. Both Comeleo et al. (1996) and King et al. (2004) showed that land use closer to the estuary had more of an impact on estuarine condition than land use further up the watershed.

In this study we used multimodel inference to develop an array regression models between each of the benthic indices and selected landscape variables to determine the relative importance of individual variables. Models were developed that did or did not account for the variation in the benthic indices within the estuary. We calculated both watershed and riparian variables for our model to assess which scale would be more related to benthic condition. Finally, we compared models equally weighting landscape variables as well as those that weighted variables closer to the estuary. Comparisons were done among these models to look at similarities and differences in benthic index response.

Materials and Methods

Watershed data

Watershed boundaries for 49 estuaries and subestuaries in the Virginian Biogeographic Province (Figure 1) were assembled in ArcGIS 9.3 (ESRI 1999–2009) using the Hydrologic Unit Code (HUC 12) NHDPlus Version 1 basin boundary data and 1:100,000 NHDPlus Version 1 stream data (nhd.usgs.gov). The watersheds ranged in size from 12 to 6701 km² (Table 1) and encompassed a wide variety of land uses. These watersheds were used as the basis for calculating landscape metrics (described below) in ArcGIS 9.3.

Road density was calculated for each watershed using the 2006 TeleAtlas roads dataset. Percent of watershed where roads were present (on a raster basis) was also calculated. Roads can negatively impact aquatic communities by altering habitat and hydrology, acting as conduits for additional contaminant loads to systems and by facilitating increased human use of an area, which can result in additional changes in land use and hydrology (Trombulak and Frissell 2000). Land use/land cover (Anderson et al. 1976) was obtained from the 2001 National Land Cover dataset (NLCD; Homer et al. 2004), converted to percent and summarized by watershed. Forested land and lands with natural vegetation are related to good ecological condition while developed and agricultural lands are often correlated with impacted aquatic communities (Dauer et al. 2000). For this analysis, land use was summarized into three main categories – developed, forested (% forest + % woody wetlands) and cultivated crops as these have been categories significantly related to benthos in previous studies (King et al. 2005a, Seitz et al. 2018).

Additional metrics associated with developed lands were also included. Percent imperviousness was obtained from the 2001 NLCD. As imperviousness increases, runoff increases, increasing pollutant delivery, while decreasing pollutant processing in soils (Arnold and Gibbons 1996). Information on location of sewage treatment plants (major dischargers) were obtained from EPA's Permit Compliance System (www.epa.gov/enviro/html/pcs). This information was converted to number of treatment plants in each watershed.

Agricultural metrics included data on practices linked to high levels of pollution and runoff. Cropland on steep slopes increases the probability of erosion and associated delivery of sediment and nutrients to nearby water bodies (O'Neill et al. 1997). Percent agriculture on steep slopes was calculated by creating a percent slope map based on 10 m elevation data available from United States Geological Survey (USGS), then calculating the percentage of agriculture (from NLCD) on 9% slope within the watershed. Studies have shown that intensive animal husbandry operations can have a detrimental effect on aquatic systems (Howarth et al. 2002, Burkholder et al. 2007). Information on farms was obtained from the 2002 United States Department of Agriculture (USDA) Census of Agriculture (www.agcensus.usda.gov) on a county basis. Data were obtained for all livestock farms as well as for large livestock farms. The definition of large farms varied by livestock type: for cows it was 500 animals, for hogs it was 1000 animals, for laying hens it was 100,000 animals and for broilers it was 500,000 animals. Because broilers can be raised to market size in six to eight weeks (Nina Bonnelycke, US EPA, personal communication), the number of broilers was divided by 5 to reflect a conservative estimate of the amount of poultry in the watershed at any given time. Farms and animals were assumed to be evenly distributed throughout agricultural land within each county. The number of farms and animals was then summarized by watershed.

Land use/land cover, imperviousness, road density, point source load and number of sewage treatment plants were also calculated within a 60 m riparian corridor along each stream within the watershed. Although the effective width of riparian buffers will vary based on width, composition and stressor, a meta-analysis by Mayer et al. (2007) showed that mean nitrogen removal was best in buffers >50 m wide. Since the NLCD has 30 m pixels, the closest corresponding width was 60 m.

To assess the importance of landscape variables closer to the estuary, inverse distance weighting (IDW) was applied to all variables. All variables were weighted by $1 / \log(\text{distance})$, a conservative weighting that does not eliminate contributions of land use not directly adjacent to the estuary. The weighting was scaled between 0 and 1 by dividing by the maximum log distance. This was done so that variables closest to the estuary would be multiplied by 1, keeping their original values. Land use/land cover, imperviousness, road density, road presence/absence, point source load and number of sewage treatment plants for the entire watershed and within a 60 m riparian buffer, and large farms and farm animals within the watershed were distance weighted. Road density was determined by calculating the length of road within a 200 m radius of a raster cell using a moving window approach (Silverman 1986), then applying IDW. Percent presence of roads was also weighted. Watershed area was similarly weighted.

Estuary Data

Benthic invertebrate abundance data from the Environmental Monitoring and Assessment Program (EMAP, www.epa.gov/emap) were assembled for this study (612 stations in 49 estuaries and subestuaries). The systems sampled included MA, NY, NJ and MD coastal bays as well as subestuaries of Narragansett Bay, the NY/NJ estuary system, Delaware Bay and Chesapeake Bay, and ranged in size from 2 to 430 km² (Table 1). These data

encompassed seven different monitoring efforts between 1997 and 2006 during the summer index period (July through early October) in the Virginian Biogeographic Province (Figure 1). These monitoring efforts used similar gear and sampling/analysis methods (U.S. EPA 2001). Most of the macroinvertebrate data were collected using a 0.04 m² Young-modified Van Veen grab. Less than two percent of the samples were collected using a 0.04 m² Ponar grab or a 0.1 m² Smith MacIntyre grab. Samples were sieved through a 0.5 mm screen, preserved in formalin and then enumerated and identified to the lowest possible taxonomic level, generally genus or species.

Invertebrates were summarized by two benthic indices – U.S. M-AMBI (Pelletier et al. 2018) and the Virginian Province benthic index (VP BI; Paul et al. 2001). U.S. M-AMBI consists of three metrics: the abundance-weighted tolerance index AMBI (Gillett et al. 2015), Shannon's H' and species richness and was calculated separately for five salinity zones (i.e., tidal freshwater, oligohaline, polyhaline, euhaline, hyperhaline; Venice System 1958). Briefly, the expectations of good and bad sites used to develop the pollution gradient applied in the factor analysis were different for each salinity zone but resulted in index results on the same scale between habitats, so the final index values could be combined across salinity zones. In the tidal freshwater habitat, species richness was replaced with % oligochaetes. U.S. M-AMBI is scaled from 0 to 1, with degraded sites being closer to zero and undegraded sites closer to one. The VP BI also consists of three metrics: salinity-normalized Gleason's D, salinity-normalized tubificid abundance, and abundance of spionid polychaetes. The salinity normalization accounted for changes in species abundance based on salinity alone (e.g. Gleason's D is higher at higher salinities and tubificids are only identified at low salinity). This is an alternative to calculating an index separately for different salinity zones. A quadratic (for Gleason's D) or exponential (for tubificids) function was used to adjust the raw values to salinity normalized values (Paul et al. 2001). Index values greater than zero are categorized as being undegraded while those less than or equal to zero are degraded. The arithmetic mean and variance of each index was calculated for each estuary or subestuary (Table 1).

Statistical analysis

Linear regression models were developed relating the benthic indices to watershed variables. All variables (Table S1) were examined using SPSS Version 24.0 (SPSS Inc, Chicago, IL, USA) to determine whether there were significant relationships between the benthic invertebrate indices and the individual independent variables ($\alpha=0.10$). An alpha of 0.10 was chosen to avoid excluding potentially important explanatory variables, and is consistent with other studies (Hale et al., 2004, Pelletier et al. 2012). To reduce the issue of multicollinearity, significant variables that were highly correlated with each other ($r > 0.70$) were eliminated.

Variables significantly correlated with one or more of the benthic indices that were uncorrelated with one another were used to develop linear regression models between the benthic indices and landscape variables in SAS 9.4 (SAS Institute 2015). Most variables were transformed to meet the assumption of homogeneity of variance. Two types of models were constructed. The first type of model used the average of the benthic indices at all

stations in each given estuary or subestuary to construct a mean model. This provided an understanding of the relationship between mean benthic condition in the estuary in relation to landscape variables. The second type of model was a weighted regression model. The landscape variables were weighted by the inverse variance of the benthic index (Zuur et al. 2009). Variance incorporated both the spatial and temporal variance within a given estuary or subestuary. This accounted for differences in benthic response within the estuary or subestuary and provided an understanding of the relationship between benthic condition in the estuary once variation in benthic response had been accounted for. Those estuaries or subestuaries with highly variable benthic response were assumed to not be responding in a consistent way to watershed impacts and were therefore down weighted in this analysis. Residuals from the models were examined for normality, homogeneity of variance, and linearity in SAS 9.4.

Models were developed for each benthic index separately, with a total of 4 models developed for each index (Figure 2). One set of models incorporated unweighted watershed variables, while the other used inverse-distance weighted landscape variables. For each of these types of models, a mean model and a model that accounted for variation in estuarine benthic condition were constructed. This provided an assessment of which variables would be most important in predicting estuarine invertebrate condition.

A model selection approach was used to select models that incorporated all possible combinations of watershed variables (Burnham and Anderson 2002, Beal 2007), resulting in a total of 254 regressions being generated for each model type. Once the models were generated, the relative importance of individual variables was determined by examining the sum of the AIC_{ω} for every model containing that variable (Burnham and Anderson 2002). AIC_{ω} are calculated as $AIC_{\omega} = \exp(-\frac{1}{2} * AIC_{\text{individual model}}) / \sum \exp(-\frac{1}{2} * AIC_{\text{all models}})$ where $AIC = AIC_{\text{individual model}} - AIC_{\text{min}}$. AIC_{ω} range from 0 to 1, with zero indicating variables appearing in 0 models and therefore having no importance to the dependent variable and 1 indicating that the variable appears in all models and therefore has maximal importance to the dependent variable. AIC_{ω} were operationally categorized so that variables with $AIC_{\omega} > 0.7$ were considered of high importance, those > 0.5 were considered of moderate importance and those < 0.5 were considered of low importance.

Model averaging (Burnham and Anderson 2002) was used to generate a composite regression equation that was used to assess the predictive ability of the models. Briefly, the AIC_{ω} for a given regression (see calculation above) was multiplied with each β coefficient in that regression. The resulting new β coefficients were then summed for each variable across all 254 regression equations. These summed β coefficients are used to create a model averaged equation. The resulting prediction from the average model is then compared to the observed values (in this case benthic index scores).

Results:

Variable reduction

Thirty-eight possible landscape variables (Table S1) were reduced to 7 uncorrelated variables (Table 2). Except for agriculture on steep slopes, all riparian variables were highly

correlated with the watershed variables (Table 3). Farm variables were highly correlated with each other (Table S2), and in turn correlated with landscape structure variables (watershed area and watershed:estuary ratio).

Landscape models without distance weighting

The importance of the individual variables in predicting each of the benthic indices was examined using the AIC_{ω} (Table 4a). For the mean U.S. M-AMBI model, estuarine area, watershed area, the watershed:estuary ratio and % impervious surface were the most important variables (Table 4a). Cultivated crops and riparian agriculture on steep slopes had moderate importance. Once estuarine variance was accounted for, the patterns change slightly (Table 4a). While % impervious surface was still highly important, estuarine area, watershed area and the watershed:estuary ratio decreased in importance, while % cultivated crops became highly important and agriculture in steep slopes in watershed increased in importance.

For the mean VP BI model, estuarine area and % impervious surface were highly important. Watershed area and the watershed:estuary ratio had moderate importance, while the remaining variables had lower importance (Table 4a). Once estuarine variance is accounted for, the patterns changed (Table 4a). Estuarine area was still highly important, but percent impervious surface decreased in importance, as did watershed area and the watershed:estuary ratio.

Landscape models with distance weighting

The importance of the distance-weighted variables in predicting each of the benthic indices was examined using the sum of AIC_{ω} (Table 4b). For the mean U.S. M-AMBI model, estuarine area, watershed area, the watershed:estuary ratio and % impervious surface were the most important variables (Table 4b). Percent of cultivated crops had moderate importance, while the remaining variables had lower importance. Once estuarine variance is accounted for, the patterns change slightly (Table 4b). Estuarine area, watershed area and % impervious surface were still highly important, but % cultivated crops and agriculture on steep slopes also became highly important. The watershed:estuary ratio decreased in importance while number of wastewater treatment plants increased in importance.

For the mean VP BI model, estuarine area, % impervious surface and number of wastewater treatment plants in the watershed were the most important variables (Table 4a). The remaining variables had lower importance. Once estuarine variance is accounted for, the patterns changed (Table 4b). While estuarine area and number of wastewater treatment plants in the watershed remained highly important, % impervious surface became less important. Agriculture on steep slopes also increased in importance. The remaining variables were of low importance to the VP BI once estuarine variance was accounted for.

Comparison of Benthic Indices

U.S. M-AMBI was significantly correlated to the VP BI ($r = 0.528$, $p < 0.0005$, Figure 3). Correspondence between index categories was good overall (76.6%) with slightly higher correspondence for poor sites (85.9%) than good sites (70.9%). The U.S. M-AMBI models

were able to explain 41% to 48% of the observed data (Figure 4), while the VP BI models only explained 6% to 37% of the observed data (Figure 5).

Discussion:

Although the benthic indices were correlated with one another, the U.S. M-AMBI models were better related to the landscape structure and land use variables than were the VP BI models, based on comparing the predicted model average results against the observed values. Given the spatial and temporal variability within the estuaries, and the fact that only landscape variables were included in the models, the adjusted R^2 of the model averaged predictions for M-AMBI ranged from 0.41 to 0.46 is quite respectable. In contrast, the VP BI model averaged predictions had adjusted R^2 from 0.35 to 0.37 when variance was not accounted for, and 0.06 to 0.26 when accounting for variance. These patterns corresponded results from the 254 individual regressions used to create the model average. While adjusted R^2 for the individual models for M-AMBI ranged from 0 to 0.94, the VP BI ranged from only 0 to 0.37, indicating that the landscape variables did not account for much of the variation in the VP BI. The VP BI models also identified far fewer variables as being highly important in predicting estuarine condition relative to the U.S. M-AMBI models. This may be because the U.S. M-AMBI index metrics incorporate more of the benthic community structure than the VP BI. The VP BI has a diversity metric and two metrics to reflect pollution tolerance - % tubificid abundance in low salinity habitats and % spionid abundance in high salinity habitats. In contrast U.S. M-AMBI incorporates an abundance-weighted tolerance index (AMBI) that integrates the pollution tolerance of the entire community in all salinity zones. In addition, U.S. M-AMBI was less variable than the VP BI; U.S. M-AMBI is bounded between 0 and 1 while the VP BI is unbounded. In this study, the raw VP BI ranged from -9.05 to 9.64, while the mean estuary VP BI score ranged from -4.12 to 1.46. These results suggest that U.S. M-AMBI is more responsive to landscape influences than the VP BI.

One of the goals of this study was to assess the utility of using watershed or riparian variables to assess estuarine condition. Riparian areas are known to be important to water quality (Mayer et al. 2007) and aquatic condition (Sponseller et al. 2001, Hale et al. 2004). However, in this study, riparian variables were highly correlated to watershed variables, suggesting that although riparian areas are functionally important, at the scale of this study (the Virginian Province), use of watershed land use variables were adequate for prediction of benthic condition. Other studies have shown that watershed variables can explain slightly more of the variation in freshwater invertebrates than riparian variables (Potter et al. 2005). It is also possible that we were not able to fully characterize the riparian area due to the 30 m resolution of the NLCD.

Another goal of this study was to compare models equally weighting landscape variables as well as those that weighted variables closer to the estuary. Although previous studies (Comeleo et al. 1996, Dauer et al. 2000, King et al. 2004) showed that land use closer to the estuary had more of an impact on estuarine condition than land use further up the watershed, for most models there were no large differences in the variables identified as being important for predicting benthic condition – whether land use closer the estuary was more highly

weighted or not. This may have been because many variables are distributed somewhat equally across the landscape, or not distributed in a gradient up and down watershed. The exception to this is the U.S. M-AMBI model incorporating estuarine variance. Although both percent impervious surface and % cultivated crops were highly important variables in both models, the importance of watershed area, estuarine area and agriculture on steep slopes increased in the model weighted by distance. It is unclear why this model is different but accounting for variance in the estuary seems to be one factor.

Although we know that estuaries tend to have distinct natural gradients from the mouth to the headwaters (Soetaert et al. 1995, Rakocinski et al. 1997), the benthic indices used in this study attempt to minimize some of the effects of these gradients by adjusting for salinity. U.S. M-AMBI is calculated for each salinity zone separately (Pelletier et al. 2018) while the VP BI uses salinity-adjusted metrics (Paul et al. 2001). Because we examined linkages between estuarine condition and the watershed, we needed to summarize estuarine condition for the entire estuary by taking the mean of all values within the estuary. This was similar to the approach of Dauer et al. (2000), who used area weighted means to look at relationships between benthic community condition and watershed variables. Other studies (Comeleo et al. 1996, Paul et al. 2002, Hale et al. 2004) used a single sampling point to represent condition in the entire estuary. Each estuary in this study was represented by at least three sampling stations to capture more of the overall condition within the estuary. Accounting for estuarine variation caused the importance of the structural variables (estuarine area, watershed area and the watershed:estuary ratio) to decrease or remain relatively stable. In contrast, the agricultural variables (% cultivated crops, agriculture on steep slopes) increased in importance or had their importance remain relatively constant when estuarine variance was accounted for. Finally, the remaining variables (% impervious surface and number of wastewater treatment plants) decreased in importance or had their importance remain relatively constant when estuarine variance was accounted for. These results suggest that future modeling should incorporate measures of estuarine variance or focus on the individual stations within the estuary.

Examination of all models for both indices indicated some commonalities among the models. Estuarine area was highly important in seven of the eight models. In general, for our study, estuary depth increased with increasing estuary area. Thus, estuarine area acted as a surrogate for estuarine volume and flushing rate (Engle et al. 2007), which will tend to improve estuarine condition. Percent impervious surface was highly important in six models. This indicator increases runoff and pollutant delivery, while decreasing pollutant processing. Increasing impervious surface is often a result of increasing development and road construction which can facilitate additional development that further impact water quality and hydrology (Arnold and Gibbons 1996, Trombulak and Frissell 2000). Watershed area, a loading surrogate, was identified as being highly or moderately important in six of eight models. The watershed:estuary ratio acts as a surrogate of concentration, balancing watershed loading and estuarine flushing. This variable was identified as highly or moderately important in half of the models. Similarly, the percent cultivated crops variable was identified as highly or moderately important in half of the models. The number of wastewater treatment plants was found to be of high or moderate importance in three out of four models. This variable was not included in the models of unweighted landscape

variables as it was correlated with the watershed:estuary ratio but was not correlated with this variable when land use was weighted by distance. Wastewater treatment plants alter hydrology (increase base flow), increase the levels of nutrients and contaminants delivered to aquatic habitats, and increase biological oxygen demand, all of which cause adverse effects to biotic communities (Paul and Meyer 2001).

The results from this study indicated that agricultural variables had the lowest impact on estuarine condition relative to the other variables considered. This may be partially explained by the fact that the models developed in this study were based on indirect relationships between individual landscape variables and benthic invertebrate condition. For example, land cover affects water chemistry and habitat of freshwater tributaries. These tributaries flow into estuaries, where they are modulated by estuarine processes and eventually affect estuarine invertebrates. Some of these indirect pathways have been explained in freshwater by King et al. (2005b) and in estuarine systems by Dauer et al. (2000). Although impervious surface showed high importance, agricultural impacts may vary widely based on individual farm practices, weather, and soil composition in the landscape.

An interesting result from this study was the importance of structural variables. Although these attributes are unchanging they have large impacts on estuarine condition. In general, larger developed watersheds have a greater potential for pollutant delivery and adverse impacts on estuarine condition. Smaller estuaries will have less potential for dilution and may be more susceptible to impact from the surrounding area. The interplay between loading and flushing can provide an initial estimate of impairment risk. These structural variables should be considered in the context of watershed and estuary planning and restoration.

Conclusion

Modeling estuarine condition indicated that inherent landscape structure (estuarine area, watershed area, watershed:estuary ratio) is important to predicting benthic invertebrate condition and needs to be considered in the context of watershed/ estuary planning and restoration. Our comparison of the two indices suggest that U.S. M-AMBI is more responsive to landscape influences than the VP BI. Although literature points to the importance of the riparian zone, our results suggest that watershed variables were adequate for assessing estuarine invertebrate condition at the scale of the biogeographic province. Variability within the estuary strongly impacts models results and suggests that future modeling should incorporate estuarine variance or focus on the individual stations within the estuary. Future studies will incorporate both structure variables, land use and estuarine variables to model benthic invertebrate condition in estuaries.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.
Watersheds in the Virginian Biogeographic Province included in this study

Figure 2.

Schematic of Study Design. Models were developed for each benthic index separately, with a total of 4 models developed for each index. One set of models incorporated unweighted watershed variables, while the other used inverse-distance weighted landscape variables. For each of these types of models, a mean model and a model that accounted for variation in estuarine benthic condition were constructed.

Figure 3.

Comparison of U.S. M-AMBI and VP BI from this study. U.S. M-AMBI ranges from 0 (Poor) to 1 (Good). The M-AMBI index can be classified as Good, Fair and Poor. VP BI is unbounded, but values ≤ 0 are Poor, while values >0 are Good.

Figure 4.

Observed versus predicted U.S. M-AMBI for each model type. a. unweighted landscape model b. unweighted landscape model accounting for variation in the benthic index within the estuary c. inverse distance weighted model d. inverse distance weighted model accounting for variation in the benthic index within the estuary

Figure 5.

Observed versus predicted VP BI for each model type. a. unweighted landscape model b. unweighted landscape model accounting for variation in the benthic index within the estuary c. inverse distance weighted model d. inverse distance weighted model accounting for variation in the benthic index within the estuary

Table 1.

Watershed and estuary area with estuarine data for all 49 estuaries in this study

Watershed	Watershed area (sq. km.)	Estuarine area (sq. km)	Number of stations	U.S. M-AMBI (mean)	U.S. M-AMBI (variance)	VP BI (mean)	VP BI (variance)
Back River (MD)	142	16	3	0.29	0.034	−0.54	0.46
Buzzards Bay	865	430	17	0.78	0.012	1.34	0.65
Cherrystone Inlet	37	5	10	0.64	0.033	−0.20	1.70
Chester River	1079	139	7	0.60	0.003	1.18	0.37
Chickahominy River	1188	26	3	0.60	0.024	1.01	0.34
Chincoteague Bay	422	299	20	0.74	0.025	0.75	1.28
Choptank River	1674	158	10	0.59	0.004	1.40	0.71
Christina River	1457	2	3	0.58	0.088	0.16	0.32
Elizabeth River	578	42	3	0.49	0.009	−0.10	0.24
Elk River	653	47	5	0.58	0.033	0.52	0.83
Gardiners Bay	57	219	4	0.86	0.001	1.09	0.83
Great Bay	1501	65	10	0.74	0.020	1.12	0.58
Great Egg Harbor	1286	51	8	0.55	0.040	0.77	1.23
Great Sound	132	39	4	0.54	0.046	−0.23	0.49
Hempstead Bay	504	65	3	0.42	0.093	−1.32	3.90
Indian River Bay	450	38	25	0.59	0.012	−0.49	4.68
Jamaica Bay	293	58	30	0.63	0.018	−1.07	2.12
Little Assawoman Bay	70	9	8	0.49	0.012	−0.03	1.09
Little Egg Harbor	265	98	9	0.70	0.010	0.39	0.66
Manokin River	253	63	3	0.86	0.006	0.81	0.19
Maurice River	991	10	4	0.58	0.105	0.95	3.90
Mobjack Bay	379	149	13	0.71	0.009	0.34	0.49
Mount Hope Bay	1481	45	14	0.61	0.018	0.34	0.56
Nanticoke River	2053	70	10	0.45	0.058	1.01	1.21
Ninigret Pond	37	8	4	0.57	0.019	−0.49	0.11
Oyster Bay	101	22	4	0.54	0.015	−0.67	0.09
Patapsco River	1517	92	7	0.55	0.018	0.99	0.48
Patuxent River	2281	127	25	0.46	0.018	0.15	0.50
Peconic Bays/Shelter Sound	542	217	6	0.79	0.022	0.83	0.69
Piankatank River	548	52	4	0.54	0.038	−0.22	0.57
Pocomoke Sound	1700	322	6	0.59	0.070	1.46	5.78
Port Jefferson Harbor	30	6	3	0.75	0.005	0.45	0.04
Providence River	2232	23	7	0.44	0.005	−2.19	5.35
Point Judith Pond	72	8	4	0.65	0.002	0.27	0.18
Rappahannock River	6662	371	38	0.52	0.017	0.32	0.94
Reed/Absecon Bay	162	54	6	0.50	0.038	−1.83	8.42
Rehobeth Bay	154	37	24	0.64	0.009	0.02	0.50
Sakonnet River	87	53	14	0.65	0.005	0.38	0.44

Watershed	Watershed area (sq. km.)	Estuarine area (sq. km)	Number of stations	U.S. M-AMBI (mean)	U.S. M-AMBI (variance)	VP BI (mean)	VP BI (variance)
Salem River	149	2	10	0.58	0.013	−0.18	8.02
Schuylkill River	4918	2	5	0.27	0.010	−4.12	13.75
Severn River (MD)	148	29	18	0.59	0.055	0.45	2.22
Sinepuxent Bay	21	20	9	0.76	0.030	0.52	1.39
South River	148	23	25	0.61	0.024	0.17	0.99
Saint Jerome Creek	12	4	6	0.78	0.006	0.04	0.30
Thames River	3792	19	3	0.54	0.053	−1.69	7.62
Warren River	178	6	5	0.40	0.024	−2.35	6.86
Westport River	280	12	3	0.62	0.005	−0.27	0.59
Wye/Wye East Rivers	205	26	3	0.47	0.022	−0.22	0.06
York River	6701	215	43	0.56	0.016	0.19	0.93

U.S. M-AMBI (multivariate AMBI index)) range from 0 to 1, with 0 indicating poor condition and 1 indicating good condition.

VP BI (Virginian Province benthic index) in this study ranges from −4.12 to 1.93. Values greater than 0 indicate good condition, while values less than or equal to 0 indicate poor condition.

Table 2.

Final landscape metrics included in benthic condition models for 49 estuaries in the Virginian Province. These variables were significantly related to benthic invertebrate condition but uncorrelated with each other.

Variables	Base model (N=7)	IDW model (N=7)	Direction of correlation with Indices	mean	min	max
Watershed area (sq. km)	x	x	–	1030	12	6701
Estuarine area (sq. km)	x	x	+	80	2	430
Watershed:estuary ratio	x	x	–	76	0	2055
Percent Impervious cover in watershed	x	x	–	8	0	63
Percent Cultivated crops in watershed	x	x	*	14	0	53
Percent Agriculture on steep (9%) slopes in watershed	x	x	–	3	0	18
Number of wastewater treatment plants in watershed		x	–	3	0	37
Percent Riparian Agriculture on steep (9%) slopes	x		–	2	0	33

* Percent cultivated crops in the watershed was negatively correlated with M-AMBI, but positively correlated with VP BI

Table 3.

Correlation between riparian and watershed variables for that particular variable (e.g., the correlation between percent impervious surface in the watershed and percent riparian impervious surface is 0.968). All variables have p-values < 0.0005.

Variable	Pearson correlation between watershed and riparian variables
Percent Impervious cover	0.968
Percent Development	0.913
Percent Forested	0.735
Percent Cultivated Crops	0.852
Number of wastewater treatment plants	0.849
Road density (m/m ²)	0.734
Percent road presence	0.786

Table 4.

Sum AIC_{ω} for Watershed and Riparian models. Higher values indicate greater importance of the variable (maximum = 1). Bolded numbers indicate variables with high importance.

a. Models Not Weighted by Distance		Mean model		Model incorporating variance	
Variables in Model	U.S. M-AMBI Landscape Model	VP BI Landscape Model	U.S. M-AMBI Landscape Model	VP BI Landscape Model	
Estuarine area	0.78	0.77	0.65	0.80	
Watershed area	0.78	0.56	0.67	0.45	
Watershed:Estuary ratio	0.77	0.58	0.66	0.39	
% Impervious surface in watershed	0.91	0.89	0.97	0.44	
% Cultivated crops in watershed	0.60	0.37	0.90	0.32	
Agriculture on steep (9%) slope in the watershed	0.31	0.33	0.48	0.45	
Riparian agriculture on steep (9%) slope	0.61	0.42	0.59	0.46	
b. Models Weighted by Distance		Mean model		Model incorporating variance	
Variables in Model	U.S. M-AMBI Landscape Model	VP BI Landscape Model	U.S. M-AMBI Landscape Model	VP BI Landscape Model	
Estuarine area	0.87	0.82	0.86	0.76	
Watershed area	0.88	0.45	0.92	0.52	
Watershed:Estuary ratio	0.73	0.47	0.46	0.47	
% Impervious surface in watershed	0.93	0.80	0.99	0.63	
% Cultivated crops in watershed	0.61	0.35	0.80	0.41	
Agriculture on steep (9%) slope in the watershed	0.41	0.32	0.74	0.66	
Number of wastewater treatment plants in watershed	0.32	0.70	0.68	0.79	

Note: AIC_{ω} are calculated as $AIC_{\omega} = \exp(-\frac{1}{2} * \Delta AIC \text{ individual model}) / \exp(-\frac{1}{2} * \Delta AIC \text{ all models})$ where $\Delta AIC = AIC \text{ individual model} - AIC \text{ min.}$