Development of a Hydrologic Model to Predict Lakeshore Phosphorus Loadings for Prediction of *Cladophora* Biomass Blooms

by

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April 2012

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Abstract

In recent years, excess phosphorus in lake water columns has triggered the nuisance growth of the filamentous green algae, *Cladophora glomerata*, in the near-shore areas of Lakes Erie, Michigan and Ontario. One approach to limiting nuisance *Cladophora* blooms is to build a systems model of the watershed hydrologic loading and aquatic biogeochemical cycling to help managers identify phosphorus control options. In this research we built the Contributing Area-Dispersal Area (CADA) weighted Export Coefficient (EC) watershed runoff model in ArcGIS to identify watershed areas delivering the greatest phosphorus loads. We tested the CADA EC model in the Lake Ontario basin using 30 arc-second digital elevation models, remotely sensed land cover classifications, and regional phosphorus export coefficients. The watershed model will be coupled with a proven aquatic biogeochemical cycling model to better assist management of nuisance algal growth along lakeshores. This simulation tool has the potential to improve nutrient tracking and eutrophication management, which may result in a much greater chance for preserving sensitive aquatic ecosystems.
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Acknowledgements

I am grateful to my honors advisor, Dr. Ted Endreny, for his enthusiasm, advice and insight throughout this project, especially with regards to the CADA-ECM, as well as for reviewing this paper. In addition, I would like to thank Dr. Lindi Quackenbush for her guidance and for reviewing this paper. I would also like to thank Dr. Jungho Im for his help with Python and ArcGIS scripting. Finally, I would like to thank my family for the support that they have shown me throughout my academic career.
Introduction

In recent years, the nuisance growth of *Cladophora glomerata*, a filamentous green algae, has increased in the near-shore areas of Lakes Erie, Michigan and Ontario, resulting in a resurgence of algal blooms (Higgins, Hecky, & Guildford, 2005). Past research has identified phosphorus as the limiting nutrient for biomass growth of *Cladophora* and effort has been put into controlling phosphorus loadings as a method of managing *Cladophora* growth (Tomlinson, Auer, Bootsma, & Owens, 2010). In order to aid in this management, Auer and Canale (1982) developed the Great Lakes Cladophora Model (GLCM) to simulate aquatic biogeochemical cycling and the relationship between ambient phosphorus levels and algal growth. Although the Great Lakes Water Quality Agreement of 1972, which introduced target phosphorus loads, has successfully reduced ambient phosphorus levels in offshore waters, there are other factors confounding the management techniques put into place (Auer et al., 2010). For example, the increased presence of zebra mussels (*Dreissena polymorpha*) has been shown to alter the underwater light conditions by increasing water clarity, thus allowing for algal growth at greater depth (Auer et al., 2010; Hecky et al., 2004). Therefore, Tomlinson et al. (2010) developed a modified version of the GLCM that is capable of determining potential *Cladophora* biomass growth levels following zebra mussel invasion.

The current form of the GLCM represents a mass balance approach that takes into account three state variables. These variables are the current *Cladophora* biomass levels, the phosphorus present in the water column (equivalent to soluble reactive phosphorus), and the phosphorus contained within the algae (Tomlinson et al., 2010); the model does not distinguish whether water column phosphorus is from allochthonous or
authochthonous sources. Within this framework, the change in *Cladophora* biomass reflects the gains through growth and losses to respiration and physical detachment. Growth is mediated by conditions of light and temperature, internal phosphorus concentration, and carrying capacity (self-shading in the work of some others). *

*Cladophora* internal phosphorus levels are a function of external phosphorus concentrations in the water column and rates of uptake are attenuated as internal phosphorus concentrations increase (Auer & Canale, 1982). The water column external phosphorus driving this is delivered to the near-shore areas by point source (PS) and non-point source (NPS) loadings, which are then exchanged with offshore waters by advection and diffusion. Within the current GLCM, these water column external phosphorus concentrations are treated as forcing conditions, meaning that they are measured in-situ for use, rather than being input as a simulated variable (Tomlinson et al., 2010). From this, it can be seen that although the GLCM is a comprehensive modeling tool capable of predicting growth potential, it is limited in its applicability by the need to input measured phosphorus levels. These limitations only allow for the use of the model as a tool for hind casting, which is most important for examining past trends causing the *Cladophora* resurgence. This idea is supported by past implementations of the GLCM, in which one of the common suggestions for improvement is to integrate the current biokinetic model with hydrodynamic and biogeochemical models (Higgins et al., 2005; Tomlinson et al., 2010). In order for the GLCM to truly be useful as a management tool, and to evaluate the effects of lake wide control, the implementation of predicted phosphorus loadings is a necessary component. This paper documents development of a watershed runoff model capable of determining phosphorus loadings delivered to lakes.
The Contributing Area Dispersal Area (CADA) Export Coefficient Model (ECM) is a conservative watershed scale model that was designed for use with readily available data to serve as a scoping tool, allowing environmental managers to make quick predictions. Based on commonly available data, this scoping model offers ease of use for managers, compared to more complex and data intensive models that take into account process hydrology and require parameterization for each study area (Endreny & Wood, 2003). The traditional export coefficient models (ECM) were designed to estimate a total annual basin phosphorus load based on fixed annual export amounts for a limited number of land cover types (Reckhow, Beaulac, & Simpson, 1980). This basic model has been expanded to vary based on many parameters including: seasonal variations in export (Hanrahan, Gledhill, House, & Worsfold, 2001); dispersal area or downslope buffering capacities (Endreny, 2002); and contributing area or topography based runoff potential (Beven & Kirkby, 1979; Endreny & Wood, 2003). The combination of the contributing area and dispersal area generates the CADA weighting scheme that creates variation in export coefficients within a single land use type and enhances spatial information of non-point source pollution via watershed phosphorus loading maps.

This research project utilizes the CADA-ECM described by Endreny and Wood (2003), to map the watershed controls on phosphorus loading and spatially identify watershed locations for non-point sources phosphorus reductions. The CADA-ECM model takes into account the three drivers of NPS pollution, which are the presence of a pollutant, the presence of run on from upslope areas and potential runoff, and the absence of pollutant trapping in downslope areas that have a low likelihood for pollutant buffering (Endreny & Wood, 2003). By incorporating these biogeophysical controls, the CADA-
ECM dynamically adjusts pollutant export coefficients to create a more comprehensive estimation of phosphorus loading, while retaining the simplicity and ease of use of the ECM. This model is then used to determine the watershed phosphorus loadings that accumulate along the lakeshore, resulting in a prediction of phosphorus concentrations that can be used within the GLCM. The remainder of this paper is organized as follows: the second section presents the CADA-ECM theory, development process, and necessary data inputs; the third section demonstrates the implementation of the CADA-ECM for the Lake Ontario watershed; and the fourth section presents a discussion of some of the many issues associated with the adaptation of this model as well as important considerations for future work.

**CADA-ECM Theory and Adaptation**

The following section details the theory behind the major components of the CADA-ECM, as well as the specific methods by which these components were implemented. The model was scripted in Python (to allow for easy future implementation with the existing GLCM) using the built in tools of ESRI ArcGIS 10 and the associated Spatial Analysis extension. Developing the model in the ArcGIS environment facilitates model use of GIS data (e.g., Digital Elevation Models (DEMs) and Land Cover Classifications) and future use by environmental managers who are familiar with the software.

**Basic CADA-ECM Theory**

The original ECM designed by Reckhow, Beaulac and Simpson (1980) utilizes land cover data to identify nutrient export coefficients and then sums the total annual land cover based nutrient loads across the watershed (i.e., this approach does not consider the
influence of contributing area and dispersal area on spatial variation in loads). This land cover based nutrient load is then combined with estimations of other nutrient sources such as septic systems, wastewater treatment plants, and precipitation to determine a total point source and non-point source watershed nutrient load. This basic model is shown in Equation 1 below, where $L_N$ is the basin nutrient load (kg/yr), $E_i$ is the export coefficient (kg/ha/yr) for land cover class $i$, $A_i$ is the area of the watershed in land cover class $i$, $S$ is the septic load (kg/yr), $W$ is the waste water load (kg/yr), and $P$ is the precipitation load (kg/yr).

$$L_N = \sum_i^M (E_i \times A_i) + S + W + P$$

The $E_i$ and $A_i$ components of this represent the NPS loading, which assumes that every land unit with identical land cover will generate the same pollutant load, regardless of the different interactions that each land area may have as a result of the upslope runoff contributing areas and downslope buffering areas. In contrast to this, the CADA-ECM model considers these governing watershed runoff factors that lead to a heterogeneous loading in the watershed.

As mentioned previously, the basic idea behind the CADA-ECM model is to take into account the presence of a pollutant for each pixel, the presence of run on from upslope areas and potential runoff, and the absence of pollutant trapping in downslope areas that have a low likelihood for pollutant buffering (Endreny & Wood, 2003). Taking these factors into account, it can be seen that the nutrient load from a pixel with a relatively high amount of runoff generation in the upslope contributing area and relatively
low nutrient trapping in the downslope dispersal area will deliver a greater load than another pixel of the same land cover type. The calculations for the contributing area and dispersal areas are described below, along with the method by which the CADA-ECM combines these two components. The general form of the CADA process can be seen in Figure 1. In addition to this, a depiction of the process flow for the CADA-ECM in ArcGIS is shown in Figure 2.

*Topographic Index Calculation*

The contributing area and slope for each pixel were used to determine that pixel’s potential for runoff as well as its saturation, based on the methods of Beven and Kirkby (1979) and Endreny and Wood (2003). The fundamental idea behind this is that the contributing area and slope represent a pixel’s degree of saturation, with saturation and runoff being more likely to occur when a pixel exhibits large contributing areas and small slopes. This slope a measure of the percent rise from the pixel to the upslope area. Using this method, a topographic index (TI) is calculated as shown below in Equation 2, where \( a \) is land cover pixel i’s upslope contributing area per contour length and \( B \) is land cover pixel i’s slope angle in fractional form.

\[
TI_i = \ln \left( \frac{a_i}{\tan B_i} \right)
\]

To perform this calculation for each pixel in the watershed, the fill, flow accumulation, flow direction, and slope routines found within ArcGIS were applied to a DEM of the delineated watershed terrain.
In order to determine the TI, the topographic sinks in the DEM are first filled using the fill function. Following this, the flow direction and flow accumulation routines are used to determine the contributing area. This product generates the numerator for Equation 2. It is important to note that ArcGIS uses the D8 method for determining flow angles, which may not be as accurate as other methods such as the multiple flow or D-Infinity methods (Endreny & Wood, 2001); however, this is the only method accessible in ArcGIS. Following this, the slope routine is used to generate the slope in the form of a percent rise at the pixel. Within this routine, pixels with a zero slope are changed to a minimum slope of 0.01% to avoid division by zero, and the resulting slope grid is divided by 100 to convert to a fractional slope rather than a percentage. In addition to this, the natural logarithm of the quotient is taken to reduce the spread of values. Finally, a watershed normalized TI is calculated as shown in Equation 3 below, where $\text{TI}_{\text{Avg}}$ is the mean watershed value of the TI.

\begin{equation}
\text{NTI}_i = \frac{\text{TI}_i}{\text{TI}_{\text{Avg}}}
\end{equation}

This is done to create a weight to ensure that the summation of final weighted ECs over the watershed is equivalent to the summation of the unweighted ECs in the traditional ECM.

**Buffer Index Calculation**

The next step in the CADA-ECM process is to calculate the Buffer Index (BI) as described by Endreney and Wood (2003), which represents the chance that a pixel has, relative to other pixels, for its downslope dispersal area to trap the polluted runoff that
may flow from that pixel. This uses the DEM and the associated overland flow paths with
a land cover map that contains the phosphorus trapping efficiency for each land cover
type. With these, it is possible to determine the dispersal area for each pixel and an
accumulated trapping efficiency within that pixel. Using this method, the BI represents a
relative measure of buffering capacity for each pixel. The BI can be expressed as shown
in Equation 4, where the numerator represents the cumulative trapping efficiency within
each pixel’s dispersal area and the denominator is the average slope of the dispersal area.

\[
BI_i = \ln \left( \frac{\sum_{DA=1}^{N} T_{DA_i}}{\tan B_{DA_i}} \right)
\]

The BI is calculated using the same basic ArcGIS functions used in the
calculation of the TI. The data inputs needed for these calculations are a land cover grid
with an attribute table of associated nutrient retention values and a DEM, which must
have a common pixel size. The first step in this process is to create a grid of land cover
based phosphorous trapping rates (0 to 100), which is a percentage representative of
buffering capacity based on literature values for phosphorous retention in different land
cover types (Endreny, 2002; Endreny & Wood, 2003). In addition to this, the trapping is
set to zero for all streams and receiving waters; this could be relaxed to allow for in-
stream deposition and represent delivery ratios lower than one. Next, the DEM is
inverted, forcing all ridges to appear as low-lying streams. The numerator of Equation 4
is then determined using the flow accumulation and flow direction routines. This flow
accumulation is also weighted by the trapping grid created previously, creating a sum of
all trapping from the receiving water to each pixel in the watershed.
Following this, the average slope of the dispersal area is calculated. The curvature command is used to determine the drop in elevation for each pixel, which is adjusted using a conditional command to convert all stream pixels to zero. This is used as a weighting grid with the inverted DEM to perform another flow accumulation, which determines the total drop in slope in the inverted DEM for every flow path. Next, the flow accumulation routine was again applied to the inverted DEM to determine the distance between each pixel and a river. The slope is calculated by dividing the drop in elevation by the length of the dispersal area. The tangent of this slope is taken and included in the BI calculation as the denominator of Equation 4. In addition to this, the natural logarithm of the quotient is taken to reduce the spread of values. Finally, a watershed normalized BI is calculated as shown in Equation 5 below, where BI<sub>Avg</sub> is the mean watershed value of the BI.

\[ NB_{l} = \frac{BI_{Avg}}{BI_{l}} \]

As with the TI, the normalization ensures that the summation of final weighted ECs over the watershed are equivalent to the summation of the unweighted ECs in the traditional ECM.

**Dynamic Export Coefficient Calculation and Final Accumulation**

The normalized topographic and buffer indices are constructed such that high values indicate a greater likelihood for hydrologically sensitive areas to exist. These normalized indices are used as weighting functions so that watershed areas with low buffering and nutrient trapping, along with larger runoff contributing areas, will represent
a greater likelihood for pollutant loading than other pixels in the watershed. Using this weighting, a spatially dynamic Export Coefficient ($EC_D$) is created. This is shown in Equation 6 below, which is applied to each pixel in the watershed.

\begin{equation}
EC_{D_i} = EC_i \times NTL_i \times NBI_i
\end{equation}

Typically, the $EC_D$ is substituted into Equation 1 to form the final CADA-ECM function that is used to determine the sensitive areas of the watershed along with the total predictions for nutrient loading within a basin. For this application, the point source components of Equation 1 are removed; to include these point sources the model user needs to collect data for wastewater treatment plant discharges. Finally, in order to determine the loading to lakeshore pixels, the ArcGIS flow direction and flow accumulation routines are used again, weighted by the newly created $EC_D$ grid. This process can be seen in Equation 7 below, which determines the nutrient load to each pixel in the same way that the original ECMs do.

\begin{equation}
L_N = \sum_{i=1}^{M} (EC_{D_i} \times A_i)
\end{equation}

By determining the total loadings to lakeshore areas, the CADA-ECM can predict the total phosphorus (TP) loadings for each pixel along the shore. Further work will need to be done to convert these loadings to soluble reactive phosphorus (SRP) concentrations, potentially through published ratios of SRP to TP, which can then be used to provide
predicted internal phosphorus concentrations for the GLCM biokinetic model. The following section describes the preliminary implementation of this CADA-ECM model.

**Implementation of the CADA-ECM**

*Study Area and Data*

The CADA-ECM was applied within the 82,990 km² mixed land cover area of the Lake Ontario watershed, in which urban and agricultural lands are the major phosphorus sources. As mentioned previously, phosphorus is considered the key nutrient for algal productivity in the Great Lakes. In addition to this, studies have found that loads of suspended phosphorus from intensive agriculture (cultivated land) and urban areas are 10 to 100 times higher than those of forested and natural lands (Sonzogni et al., 1980). Analysis of land usage in the Great Lakes region has shown that agricultural land makes up about one-third of the total land, with the Lake Ontario watershed possessing a large portion of the land (Sonzogni et al., 1980). Based on this, the Lake Ontario watershed was chosen for the preliminary examination of the use of the CADA-ECM for predicting phosphorus loadings.

Datasets used to implement the CADA-ECM routine in the Lake Ontario watershed were retrieved from multiple sources. The first of these was a Shuttle Radar Topography Mission (SRTM) 30 arc-second (~800m pixel size) digital elevation model clipped to the Lake Ontario watershed (Farr et al., 2007). In addition, land cover data from the 2001 National Land Cover Data from the (resampled to 800m pixel size) (Figure 3) was obtained for the U.S. portion of the watershed (Homer, Huang, Yang, Wylie, & Coan, 2004). The decision not to include the Canadian portion of the Lake Ontario watershed was made based on resources available at the time of development. Future
work should consider the Canadian portion of the watershed to provide a more complete estimate of the phosphorus loadings. Finally, published median values for phosphorus export coefficients and nutrient retention in the Great Lakes, shown in Table 1, were used (Endreny & Wood, 2003; Sonzogni et al., 1980). These limited data needs are an important feature of the CADA-ECM and the availability of these data for most areas will help the model’s applicability for the Great Lakes and other watersheds where the GLCM may be applied.

**Accumulated Lakeshore Phosphorus Loading Estimates**

Results were obtained by applying the previously described process to the Lake Ontario watershed data. The normalized Topographic Index (Figure 4) illustrates the spatial variation in runoff potential for each Lake Ontario watershed pixel, showing how the relatively flat, large contributing area river areas have the greatest TI values. The normalized Buffer Index (Figure 5) indicates areas with below average buffering that are contributing significantly to the transport of P in the watershed. When these two intermediate products were combined, the CADA-ECM estimates of the total annual phosphorus loading were determined (Figure 6). In addition to the accumulated loadings within the entire watershed, it can be seen that for the areas with low buffering capacity (BI) and a high potential for runoff (TI), the total P accumulation rises quickly, allowing for transport through rivers to the shore of the lake. Given the focus of this project is on the loadings for lakeshore pixels, these are the ones that should be considered. Along most areas of the lakeshore, it can be seen that a majority of the large phosphorus loads are delivered through distinct rivers, with the largest accumulations occurring away from
the shore of the lake. This is likely due to the large extent of agricultural land in the southern portion of the watershed.

Although the purpose of the CADA-ECM adaptation described here was to predict loadings for use in the GLCM, the model can be used as a standalone product as well. The three data products described above could be useful for environmental managers, as they can show origins of higher phosphorus loadings, potentially indicating areas in need of management. Using this process, the CADA-ECM provides a reasonable and easy-to-use scoping tool for targeting and ultimately managing the most critical NPS loads and to aid in the prediction of Cladophora blooms.

**Discussion and Future Improvements**

When examining the applicability of this model, consideration should be given to the uncertainty of export coefficients. The model used median published values for phosphorus export coefficients and nutrient retention in the Great Lakes (Endreny & Wood, 2003; Sonzogni et al., 1980), but in each of these studies cited, a range of values were provided. Past applications of this model have noted these uncertainties; however, methods exist to account for them, including the use of erosion scaled export coefficients or randomized simulations with a range of export coefficients (Endreny & Wood, 2003; Khadam & Kaluarachchi, 2006; Reckhow et al., 1980). Since the model has not gone through any form of validation, it is unclear whether the selection of these median values was most appropriate for the watershed. In the future, it would be beneficial to obtain annual phosphorus loading data on the shores of Lake Ontario (based on historic records or new sampling), especially in the areas of high loading shown in Figure 6. Comparing these measured values to the model predictions would allow evaluation of the selection of
export coefficients and nutrient retention values. It is important to note, though, that this uncertainty is not seen as a major issue for the current application, as this model is designed purely as a scoping tool. If highly accurate predictions are required, other models allowing for parameterization of the specific hydrologic processes in the watershed would be needed.

In order to use this scoping model in management applications, it would also be useful to provide a bounded range of NPS loading estimates that represent the uncertainty in the selected data values that were used in the CADA-ECM (Reckhow et al., 1980). This could be done in a variety of ways, but it would likely be best to follow the methods of Endreny and Wood (2003) by performing a series of random simulations that make use of minimum, lower quartile, median, upper quartile, and maximum values for phosphorus export coefficients and nutrient retention at each land cover type. By performing a large number of simulations, a range of total phosphorus accumulations could be generated for the lakeshore pixels. This would be useful for the implementation with the GLCM, as it would provide a comprehensive estimate of the degree to which a harmful algal bloom may occur, given a variety of possible land cover based phosphorus inputs.

Another shortcoming of the current formulation is that it only takes into account the non-point source components of the ECM (Equation 1). Based on the analysis of Endreny and Wood (2003), in order to obtain an accurate estimate for the accumulated loading, it is important that a reasonable proportion of total phosphorus loading is included from each of the potential categories, which includes wastewater treatment facilities, onsite sewage treatment and disposal systems, land cover based sources, and dairy manure. Of these categories, the only one considered in this model was the NPS
land-cover-based sources. The reason for this is the significant amount of data collection required to account for each of these sources, which did not fit the time constraints of the current project. Although the model can still act as a general scoping model, the loading predictions may be less accurate without additional data (Reckhow et al., 1980). Adding the point source components to the model would generate better estimates of the accumulated loadings that are delivered to Lake Ontario. In addition to this, as previously mentioned no data was included for the Canadian portion of the Lake Ontario watershed. Depending on the needs of future applications, the inclusion of this data may be useful to get a better estimate of the lakeshore accumulations for the entire lake. Including this data may complicate the model inputs though, making it more difficult for managers to implement the model within their own areas of interest. Because of this, it is important for future applications to consider the intended use of the model and to base the need for additional data on this use.

Along with these issues, the development of the CADA-ECM model in Python for ArcGIS also created several obstacles. Python was used for the scripting of this model, rather than the Model Builder within ArcGIS, mainly because all ArcGIS functions are available in Python and the use of a popular scripting language allows for easier future integration with the GLCM. Despite this ease of use, it was often difficult to translate the CADA-ECM algorithm into Python and because of this, a significant amount of time was spent debugging minor errors in the model syntax. Specifically, there was limited ESRI documentation to guide the translation of the Arc Macro Language used by Endreny and Wood (2003) into the proper Python syntax. In order to make this
model more accessible for future modifications, the model code (with comments) is provided in Appendix C.

Implementation of CADA-ECM in Python has also been limited to a single test case, and improvements are required in algorithms and methods to determine the indices and dynamic export coefficients. As an example, the normalized BI displayed in Figure 5 shows a number of pixels for which no BI was calculated. The likely cause of this is that ArcGIS allows for division by zero, resulting in a NODATA value being assigned to the specific pixel. This occurs in many of the inland lakes where the slope of the dispersal area is essentially zero. Once the NODATA value appears for a pixel, it will carry though the remainder of the calculations, causing any potential phosphorus contribution from this pixel to be eliminated. This represents a major issue with the current model and the specific causes of this will need to be determined and altered in future work.
Conclusion

The Contributing Area and Dispersal Area Export Coefficient Model (CADA-ECM) was developed to predict accumulations of nonpoint source (NPS) phosphorous loading to lakeshore areas. By using the CADA weighting scheme, the model can account for the effects that buffering and runoff potential have on the phosphorus loadings. This paper describes a watershed runoff model capable of determining phosphorus loadings delivered to lakes. In addition to this, the model can be used to identify the most critical NPS pollution areas within the watershed. The major benefit of using this CADA-ECM, like other biogeophysical-based scoping models, to explore the extent of NPS runoff is that they allow for a relatively fast and easily computed series of predictions that can be used to target areas for further analysis with more complex process-based modeling or with management techniques. Through this research, the primary goal of this model, which was to use the watershed phosphorous runoff hydrology to target areas of high loading that may result in harmful Cladophora blooms, has been met. Future improvement of this model will include the integration of the current biokinetic model (GLCM) with CADA-ECM to provide a comprehensive management tool that can be adapted and applied to areas of interest within the Great Lakes or other areas experiencing similar resurgences of algal growth.
References


Figure 1: Schematic of the CADA process for determination of the fate of land source pollutants. The upslope area determines the runoff likelihood and the downslope area determines filtering likelihood. (Endreny and Wood 2003)
Figure 2: General flow of the CADA-ECM as constructed in ArcGIS
Figure 3: Watershed NLCD data, resampled to an 800m resolution. Values of phosphorus retention (%) and export (kg/pixel/yr) were assigned to each class.
Figure 4: Normalized Topographic Index (TI). A high TI indicates greater likelihood of runoff and subsequent pollutant discharge to waterways.
Figure 5: Normalized Buffer Index (BI). A low BI indicates greater chance for pollutant discharge to waterways.
Figure 6: Natural log of total phosphorus accumulation for each pixel in the watershed. Of interest to this project are the pixels along the lakeshore, which represent the total amount of P entering the lake. In these areas of high loading, the GLCM will be used to predict dangerous blooms.
Table 1: Selected export coefficients and phosphorus retention values for each NLCD land cover classification (Endreny & Wood, 2003; Sonzogni et al., 1980).

<table>
<thead>
<tr>
<th>Name</th>
<th>Export Coefficient (kg/ha/yr)</th>
<th>Phosphorus Retention (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open Water</td>
<td>0.000</td>
<td>0</td>
</tr>
<tr>
<td>Developed, Open Space</td>
<td>0.925</td>
<td>0</td>
</tr>
<tr>
<td>Developed, Low Intensity</td>
<td>0.925</td>
<td>0</td>
</tr>
<tr>
<td>Developed, Medium Intensity</td>
<td>0.925</td>
<td>0</td>
</tr>
<tr>
<td>Developed, High Intensity</td>
<td>0.925</td>
<td>0</td>
</tr>
<tr>
<td>Barren Land</td>
<td>0.150</td>
<td>0</td>
</tr>
<tr>
<td>Deciduous Forest</td>
<td>0.140</td>
<td>30</td>
</tr>
<tr>
<td>Evergreen Forest</td>
<td>0.200</td>
<td>30</td>
</tr>
<tr>
<td>Mixed Forest</td>
<td>0.170</td>
<td>30</td>
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<tr>
<td>Scrub/Shrub</td>
<td>0.208</td>
<td>56</td>
</tr>
<tr>
<td>Grassland</td>
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<td>56</td>
</tr>
<tr>
<td>Pasture/Hay/Alfalfa</td>
<td>0.250</td>
<td>0</td>
</tr>
<tr>
<td>Cultivated Crops</td>
<td>0.950</td>
<td>0</td>
</tr>
<tr>
<td>Woody Wetlands</td>
<td>0.000</td>
<td>42</td>
</tr>
<tr>
<td>Emergent Wetlands</td>
<td>0.000</td>
<td>42</td>
</tr>
</tbody>
</table>
Appendix C – Model Code

```python
# Title: Contributing Area Dispersal Area Export Coefficient Model (CADA-ECH)
# for ArcGIS
# Description: Performs a series of calculations to determine the accumulation
# of P in a given lake watershed
# Requirements: ArcGIS 10, Spatial Analyst Extension
# Author: Colby Fisher
# Last Edited: 4/23/2012

import arcpy
import env
from arcpy.sa import *
arcpy.env.overwriteOutput = True  # Allow Python to overwrite files

# Check out the ArcGIS Spatial Analyst extension license
arcpy.CheckOutExtension("Spatial")

# Workspace settings (adjust this for different computers)
env.workspace = "C:/Ontario_Trial/Data/"

# Set local variables
This DEM is a 30' DEM, clipped around 800m pixel size DEM, clipped around
# delineated watershed
inDEM = "osi_utshdddens"

# File Definitions
This file needs to be created outside of a function below so that
it can be written to
TmpRise = "C:/Ontario_Trial/Data/Tmprise"

# Preliminary Calculations
Create Grid Weight File
Rivers are cells receiving > 300 pixels
River pixels set to 0 while other pixels are set to DEM res of 800m
Process will then: Fill DEM, calculate flow direction, and calculate
flow accumulation

filledDEM = Fill(inDEM)

print("Fill Complete")
flowDirec = FlowDirection(inDEM)
print("Direc Complete")
flowacc = FlowAccumulation(flowDirec)
print("Accum Complete")

Create Weight grid that assigns a value of 0 to pixels that make up the lake,
# based on DEM elevations
Would need to change threshold value for other DEMs
Weight = Con(filledDEM, 1, 0, "VALUE > 78")
Weight.save("C:/Ontario_Trial/Output/Weight")

# Create image of the basic, cell weighted, flow accumulation
FlowAccedit = Times(flowacc, Weight)
FlowAccedit.save("C:/Ontario_Trial/Output/FlowAccedit")
```

27
# Execute Conditional to assign cell size weight to non river cells
65 river0 = Con(flowacc, 0, 800, "VALUE > 300")

68 print("Con Complete")

71 # Topographic Index (TI) Calculation
72 #---------------------------------------------------------------------
73 # Determine the local pixel slope as a percent rise
74 # For pixels with a zero slope, assign a the minimum slope of 2.125%
75 # Divide by 100 to convert to a decimal slope
76 slp = Con(Slope(filledDEM,"PERCENT_RISE"),(2.125/100),Divide(Slope(filledDEM,"PERCENT_RISE"),100),"VALUE = 0")

80 # Determine the Topographic Index for each cell
81 TI = ln(A/sl) where A is the weighted accumulation area and Sl is
82 # the local pixel slope as determined above
84 $TI = ln(Divide(FloodAccumulation(FloodDirection(filledDEM),river0)),slp))
86 $TI.save("C:/Ontario_Trial/Output/TI")
88 print("TI Complete")
90
91 # Buffer Index (BI) Calculation
94 #---------------------------------------------------------------------
96 # Negate the DEM
97 negDEM = filledDEM * -1
99 # Determining the average slope for each of the pixel's dispersal area
100 # Based on the basic slope = rise/run principle
102
104 # RISE
106 #---------------------------------------------------------------------
107 # Determine the change in elevation between the pixel and the river pixel
108 # Uses the ArcGIS curvature and con commands
109 # The curvature tool will calculate the second derivative value of the input
110 # Surface at each pixel and then fit a fourth order polynomial to this to
111 # determine the curvature
112 # If not at a river a value of tmprise is assigned
113 tmprise = Con(river0, 0, tmprise, "VALUE <> 0")
114 ifnnotasc = Con(tmprise, "VALUE <> 0")
115
116 # Create a raster that is the sum of elevation change between the pixel and
118 # the nearest river cell
119 tmprise = FlowAccumulation(FloodDirection(filledDEM),tmprise)
120
121 # Assign riparian cells (zero slope) to a minimum elevation change and set this
122 # as the final RISE using the Con command:
123 if false - use the slope command to assign a percent rise value from the negDEM
125 if false - use the value from the previously created raster
126 rise = Con(tmprise, Slope(negDEM), tmp3rise, "VALUE = 0")
127 print("Rise Complete")
### Determine the sum of the distance from each ridge cell (valleys in the negDem)

138 RN = FlowAccumulation(FlowDirection(negDEM), river0)

139 Print("Run Complete")

140 Determine the final slope for each pixel area, 0.1 in rivers

141 hillslope = Con(river0, 0.1, Divide(rise, run), "VALUE = 0")

142 Print("Hillslope Complete")

143

### Nutrient Trapping Potential

148 # Extract Land Use info

149 landuse = Lookup("LandCoverClipProj.tif", "PRelease")

150 # Nutrient Release

151 # Use the table of nutrient values for P from the land use classification to

152 # specify the potential contribution from that specific cell as a percent

153 # using values from Souungi et al. 1988 in percentages

154 # Determine P retention from the nutrient release values used (in % form)

155 tmpfilter = (100 - landuse)

156 # Set P retention values to 0 in all cells that are classified as rivers

157 tmpfilter = Con(river0, 0, tmpfilter, "VALUE = 0")

158 # Use the flow accumulation routine to determine the nutrient trapping

159 efficiency = FlowDirection(negDEM, tmpfilter)

160 tmpfilter = FlowAccumulation(FlowDirection(negDEM, tmpfilter)

161 tmpfilter.save("C:/Ontario_Trial/Output/tmpfilter")

162 # Use the con command to set a minimum trapping value of greater than or equal

163 # to 1 for all non river cells (add 1)

164 tmpfilter = Con(tmpfilter, Con(river0, (tmpfilter + 1), tmpfilter, "VALUE <> 0"), tmpfilter, "VALUE <> 1.1")

165 # Use the con command to set a trapping value of 1 for all river cells

166 Filter1 = Con(river0, 1, tmpfilter, "VALUE = 0")

167 # This is done to avoid division by zero

168 BI = ln(filtered / hillslope)

169 BI.save("C:/Ontario_Trial/Output/BI")

170 Print("BI Complete")

171 # Determine Dynamic Export Coefficient Values

172 # Calculate the final BI, where BI = ln(filtered / hillslope)

173 BI = ln(Divide(filter1, hillslope))

174 BI = (filter1, hillslope)

175 BI.save("C:/Ontario_Trial/Output/BI")

176 Print("BI Complete")

177 # Calculate average BI and TI to use for normalized indices

178 # Calculate statistics for the rasters

179 # (This function will exclude NODATA cells within the watershed)

180 Extract the mean from the statistics and convert to a floating point number

181 arcpy.CalculateStatistics_management(TI)
192 TIMean = float(str(arcpy.GetRasterProperties_management(TI, "MEAN")))
193
194 arcpy.CalculateStatistics_management(BI)
195 BIMean = float(str(arcpy.GetRasterProperties_management(BI, "MEAN")))
196
197 # Generate image of normalized TI and BI for display
198 TIm = Divide(TI, TImean)
199 TIm.save("C:/Ontario_Trial/Output/TI")
200 BIm = Divide(BIMean, BI)
201 BIm.save("C:/Ontario_Trial/Output/BI")
202
203 print("Averages Complete")
204
205 # Determine the Dynamic Export Coefficient (ECd), where:
206 # ECd = EC*(TI/TImean)*(BImean/BI) for each cell
207
208 # Nutrient Release
209 # Use the table of nutrient release values for P from the land use classification
210 # to specify the amount contributed from that specific cell
211 # Using values from Sonzongi et al. 1988 (units of kg/ha/yr) and that have been
212 # transformed to units of kg/pixel/yr (6400000m^2/pixel)/(10000m^2/ha)
213 ECd = Lookup("LandCoverClipProj.tif","PMblue")
214
215 ECd = Times(Times(Divide(TI, TImean), Divide(BImean, BI)), EC)
216 ECd.save("C:/Ontario_Trial/Output/ECd")
217
218 print("ECd Complete")
219
220 #========================================================================
221 # Use Dynamic EC Values as weighting grid for final flow accumulation
222 # Use natural log to reduce spread of results for visual presentation
223 # Using the weighting grid created earlier will also remove the routing across
224 # the lake surface, showing only the accumulation up to the shore pixels
225
226 FlowAcc = FlowAccumulation(FillDirection(filledDEM), ECd, Weight)
227 FlowAcc.save("C:/Ontario_Trial/Output/FlowAcc")
228
229 # Transform the final accumulations for better display
230 lnFlowAcc = Ln(FlowAcc)
231 lnFlowAcc.save("C:/Ontario_Trial/Output/lnFlowAcc")
232
233 print("FlowAcc Complete")
234
235
236
237