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# Effects of future urban and biofuel crop expansions on the riverine export of phosphorus to the Laurentian Great Lakes

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ABSTRACT

Increased phosphorus (P) loadings threaten the health of the world's largest freshwater resource, the Laurentian Great Lakes (GL). To understand the linkages between land use and P delivery, we coupled two spatially explicit models, the landscape-scale SPARROW P fate and transport watershed model and the Land Transformation Model (LTM) land use change model, to predict future P export from nonpoint and point sources caused by changes in land use. According to LTM predictions over the period 2010–2040, the GL region of the U.S. may experience a doubling of urbanized areas and agricultural areas may increase by 10%, due to biofuel feedstock cultivation. These land use changes are predicted to increase P loadings from the U.S. side of the GL basin by 3.5–9.5%, depending on the Lake watershed and development scenario. The exception is Lake Ontario, where loading is predicted to decrease by 1.8% for one scenario, due to population losses in the drainage area. Overall, urban expansion is estimated to increase P loadings by 3.4%. Agricultural expansion associated with predicted biofuel feedstock cultivation is predicted to increase P loadings by an additional 2.4%. Watersheds that export P most efficiently and thus are the most vulnerable to increases in P sources tend to be found along southern Lake Ontario, southeastern Lake Erie, western Lake Michigan, and southwestern Lake Superior where watershed areas are concentrated along the coastline with shorter flow paths. In contrast, watersheds with high soil permeabilities, fractions of land underlain by tile drains, and long distances to the GL are less vulnerable.


## 1. Introduction

The Laurentian Great Lakes (GL, see Fig. 1) contain 18% of available global fresh surface water. Approximately 10% of the U.S. population lives in the GL basin contributing watersheds, supporting a non-farm economy of $3.7 trillion gross domestic product (GDP), which is 30% of the GDP for the U.S. and Canada combined (USEPA, 2009; Austin et al., 2007; Grunwald and Qi, 2006; Krantzberg and de Boer, 2006). While the importance of the freshwater resources in the Great Lakes cannot be overstated, the GL continue to experience ecosystem impacts from anthropogenic disturbances.

The Great Lakes receive water and accompanying nutrients from many tributaries draining areas ranging with forests, intensive farming, and large urban centers. Nutrient input from these tributaries is extremely variable (Robertson and Saad, 2011). The nutrient loading has caused eutrophication to various degrees, including excessive growth of planktonic and attached algae, turbidity, changes in biotic composition, undesirable taste and odor, and promotion of anoxic conditions to various degrees (Pauer et al., 2011; Evans et al., 2011; Michalak et al., 2013; Zhou et al., 2013). Policies and programs put into place to protect GL water quality date back to 1972 with the GL Water Quality Agreement (GLWQA) signed jointly by the U.S. and Canada and amended in 1978, 1987, and most recently in 2012 (GLWQA, 2012). The GLWQA has identified phosphorus (P) as the nutrient of primary concern for eutrophication in the Great Lakes and defined target P loads for each lake.

The U.S. Environmental Protection Agency (USEPA) has also developed a national strategy to reduce concentrations of P by establishing waterbody-specific nutrient criteria, including the Great Lakes (USEPA, 1998). Although reductions in loading have reduced most open-lake eutrophication problems, except for Lake Erie, eutrophication problems are still common in many nearshore areas and embayments (Michalak et al., 2013).

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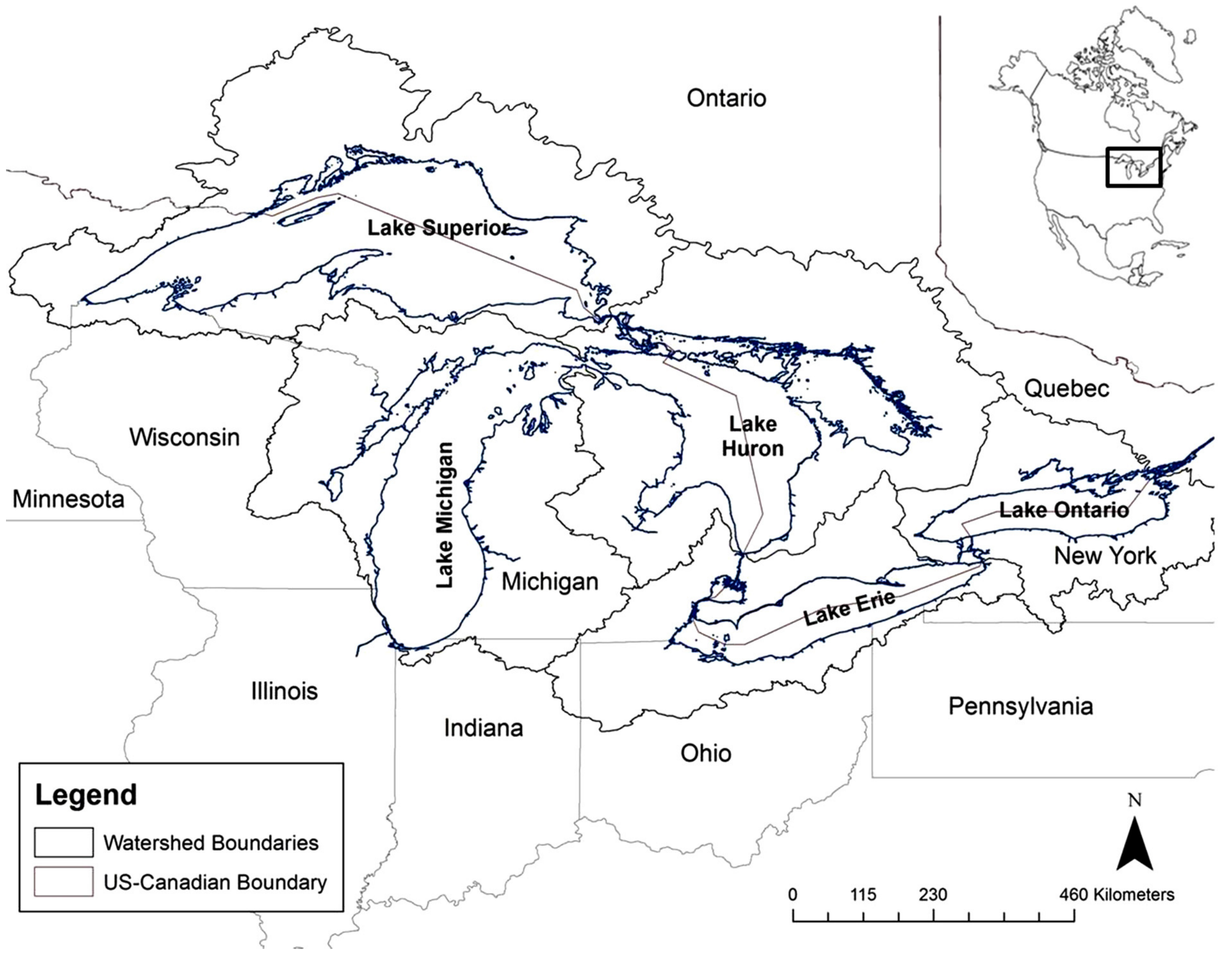


**Fig. 1.** Location map for the Laurentian Great Lakes.

Descriptions of nutrient sources are typically made in terms of point sources, which usually emanate from a pipe or well-defined outlet, and nonpoint sources, which tend to reach streams via runoff from the land surface. The current paradigm is that the majority of P loads emanating from the GL watersheds are derived from nonpoint agricultural sources (Robertson and Saad, 2011; Auer et al., 2010); however, at a local scale, inputs from point sources are still significant (Robertson and Saad, 2011).

Land use in the GL basin has changed rather dramatically over recent decades (Nechyba and Walsh, 2004; Greene, 1997). From the 1970s to 2000s, Pijanowski and Robinson (2011) found that in three major metropolitan areas of the Upper GL basin (Detroit, Chicago, and Milwaukee), along with the Muskegon, Michigan, area, urban land use approximately doubled while agricultural land use decreased. If the trends in growth of the urban areas and population continue in the future, P exports to the GL in the future could change (Southworth et al., 2007). Furthermore, potential agricultural intensification, due to, for example, biofuel feedstock crops, could counteract recent regional decreases in agricultural land use (Plourde et al., 2013), also leading to potential increases in P loading to the GL.

Predictive tools are needed to help understand the complex interaction between land use change, human activities, and P loads (units of mass per time). Given limited resources for restoration and mitigation, these tools that can identify high impact areas across the GL basin could be used to prioritize management efforts. Traditional analytical approaches for assessing the impacts of human activities on water quality have been based on the development of detailed, predictive models (Johnes, 1996). Modeling nutrient loads in watersheds typically relies on one of two techniques: deterministic modeling or statistical modeling. Process-based deterministic models simulate nutrient transport in watersheds based on relationships between land use characteristics and nutrient sources, migration of nutrients to adjacent waterways, and fate and transport in the waterways. In deterministic export-coefficient modeling, rates of nutrient delivery from a variety of sources are provided as model inputs and corresponding fractional export coefficients are used to estimate loading rates to adjacent waterways (Johnes, 1996; Young et al., 1996; McGuckin et al., 1999; Johnes and Heathwaite, 1997). In contrast, statistical models are based on regression-derived relations between flows, nutrient loads, and environmental characteristics (Daly et al., 2002).

Many studies have used deterministic models to simulate water quality at the catchment scale in the GL basin, including the Soil and Water Assessment Tool (Arnold et al., 1998; Bosch et al., 2013). The spatially explicit SPARROW (SPAtially Referenced Regression On Watershed attributes) model has been used to model water quality constituents at regional scales (Preston et al., 2011), including the GL basin (Robertson and Saad, 2011).

Exploration of the impacts of land use and land cover change on water quality has been accomplished previously by coupling land use cover change models, including the artificial neural network-based LTM (Tayyebi et al., 2012; Pijanowski et al., 2002a,b; Tang et al., 2005) (used in this study) combined with water quality models. The limitations of these previous studies are that they do not: (a) assess the impacts of expanding agriculture on P loadings,

(b) provide assessments of land use impacts on P loads at regional scales or (c) allow separate parameterization of export from specific land use classes, limiting their ability to examine relative contributions of urban and agricultural land uses to loadings and to discriminate contributions from point and non-point sources of P.

In this paper, we first estimate the specific changes in future P sources caused by predicted changes in land use and then estimate the resulting riverine P loadings for the watersheds across the U.S. portion of the GL basin, for a 2010 base year and 2040. We employ the LTM to generate two scenarios that follow historic and future growth trends: urban expansion (UE) and urban expansion plus expanded biofuel feedstock cultivation (UE + BF). These two changes in land use are then used to estimate changes in P sources to the landscape. We link land use categories and population to estimate future P source magnitudes, based on the two land use scenarios. These changes in P sources are then input into a calibrated SPARROW model for the upper Midwestern part of the U.S. (Robertson and Saad, 2011), which is then used to estimate future changes in spatially distributed P loads based on changes in P source magnitudes. The predicted P loads are examined at several spatial scales, including the five GL basins and Hydrologic Unit Code 8 (HUC8s) (Seaber et al., 1987) watersheds. Finally, we identify the sites most vulnerable to changes in future loading conditions, in terms of potential to contribute P loads to the GL. The advance of this work over previous modeling studies of P exports in the GL is the assessment of the impacts of anticipated, future land use change based on spatially explicit representations of P-landscape interactions and future changes in P sources.

## 2. Methods

### 2.1. Modeling framework

The two basic components of the modeling system are a spatially distributed land use change model (LTM) and a watershed-based P fate and transport model (SPARROW). The models are coupled through relationships between land use categories and P source terms, resulting in spatially distributed predictions of annual P loadings at the catchment scale. P loading predictions at the catchment scale are aggregated to larger watersheds through a stream network within SPARROW. The flow of information in the modeling system is conceptually illustrated in Fig. 2.

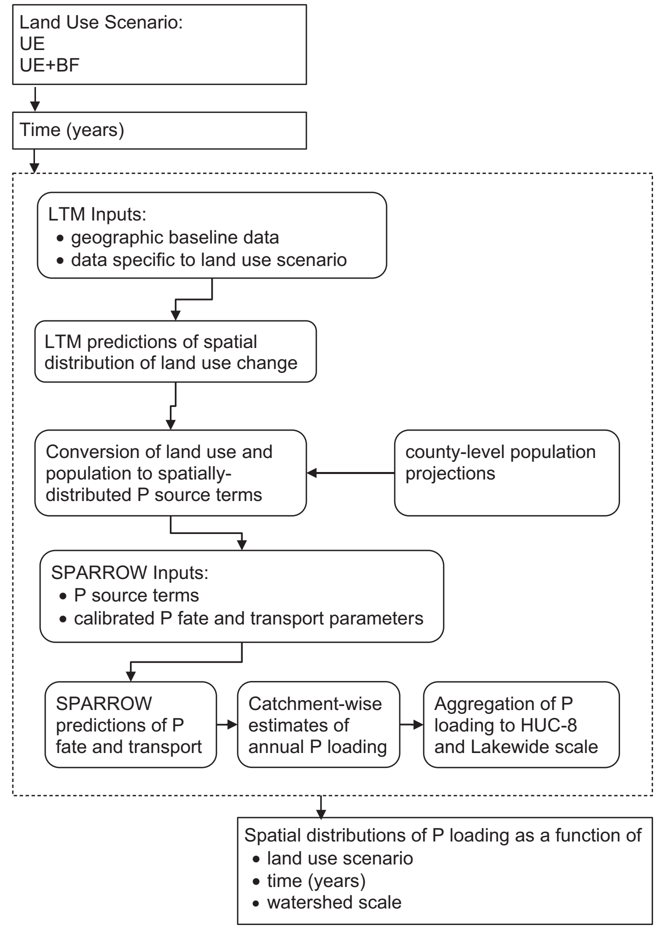


**Fig. 2.** Schematic diagram of modeling framework.

### 2.2. Land transformation model

The LTM is an artificial neural network (ANN) and GIS-based land change model that is used to forecast (e.g., Pijanowski et al., 2002b, 2005a; Tayyebi et al., 2011a) and backcast land use changes (Ray and Pijanowski, 2010) for land use planning and natural resource management. The LTM has been applied and calibrated for a variety of locations across the United States (most recently, Wiley et al., 2010; Yang et al., 2010; Tayyebi et al., 2012), Europe (Pijanowski et al., 2006), Asia (Tayyebi et al., 2011b), and Africa (Moore et al., 2012).

The LTM uses an ANN to learn about the spatial relationships between inputs (drivers of change) and output (locations of urban change). For the LTM urban simulation used here (UE), input maps were created from public domain GIS data, such as roads, rivers, digital elevation models, and locations of cities, towns, and so on. The ANN was configured with one hidden layer and weights between all nodes of the network. A feed-forward, back propagation learning procedure was configured such that weights between nodes of the neural network were adjusted with each pass and output values estimated the data. Mean square errors (MSE) were calculated for all estimated and observed output values, with a delta rule applied to adjust weights (Widrow and Lehr, 1990) and the process was repeated. The training is stopped when a global MSE minimum is reached. For nearly all LTM applications, MSE stabilizes between 50,000 and 100,000 cycles (Pijanowski et al., 2005b, 2006; Pijanowski and Robinson, 2011).

Urban land use change from 2010 to 2040 for the UE and UE + BF scenarios were generated using the following procedure (Fig. 3). First, the final neural network weights were used to create a map of the estimated of urban change potential. Second, the quantity of urban change was estimated using Thiessen polygons created from point data of locations of cities, towns, and villages from the U.S. Census Places database (U.S. Census Bureau, 2010). Next, a multiple generalized linear regression model was used to quantify urban growth for place polygons as a function of initial urban size, polygon size, size of adjacent polygons, initial adjacent urban size, and place polygon population change. Then, statewide population growth projections were scaled to each place and used to quantity the per capita urban change estimated for each time step and urban change rates. These forecasts were then applied to the 2006 NLCD (National Land Cover Database, USGS, 2011) and location and the quantity errors (see Tayyebi et al., 2012) were minimized across several spatial scales. For the LTM forecasts used here, we employed NLCD data from 1992 and 2001 to build the model and then saved the neural network weights applied to the 2001 data to forecast to 2006.

The model was able to predict urban use in 2006 with a 90% correct location goodness of fit at a 3-km resolution (Tayyebi et al., 2012; Pijanowski et al., 2014). The locations of urban change were

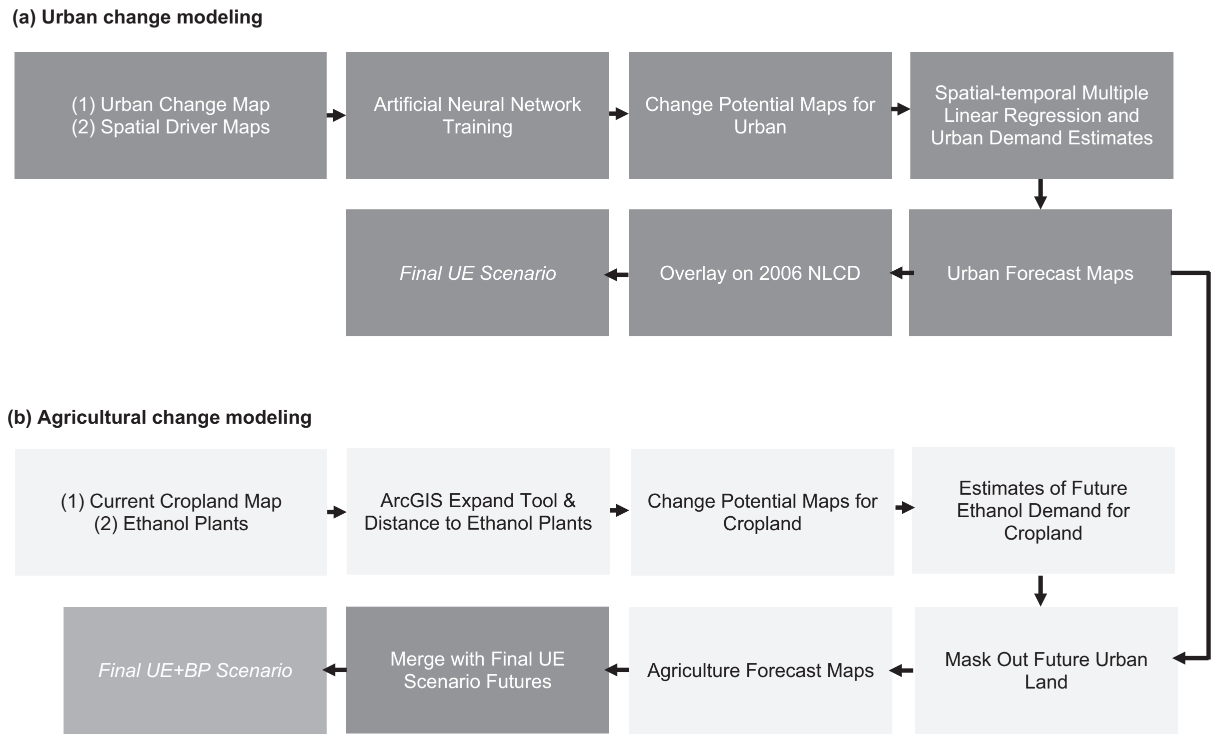


**Fig. 3.** Schematic description of LTM (a) urban land use change modeling and (b) agricultural land use change modeling.

then used to update urban use for each time step from 2010 to 2040 in ten year increments, resulting in the UE land use scenario maps.

Forecasts of agricultural expansion due to biofuel feedstock cultivation were combined with the urban land forecasts to produce the UE + BF scenario maps (Fig. 3(b)). Future urban locations were masked using the GIS and remaining arable lands (i.e., non-open water, non-public, and locations with slopes less than 8%) were considered as candidate locations for agriculture expansion. Average corn yields from 2007 through 2011 and estimates of ethanol production needed to reach 2010 and 2040 Renewal Fuel Standard targets (USDA, 2012; Plourde et al., 2013) were used to calculate future cropland demand. Current locations of ethanol processing plants were used to calculate distance from the nearest plants using the GIS *expand* tool. The final cropland forecast map was created to match the total land area needed in the future with the potential arable cells nearest to current ethanol plants having with greatest priority to change.

### 2.3. SPARROW model

SPARROW is a regional watershed model that uses a non-conservative transport and mass-balance approach to predict long-term average-annual loads of P (units of kg/year) based on P sources and transport and fate processes, in terrestrial and aquatic ecosystems (Smith et al., 1997; Schwarz et al., 2006; Alexander et al., 2008). Nutrient fluxes are attenuated or decayed as the nutrients travel through a given stream network, via loss terms that account for decay in streams or reservoirs.

Predictions of mean-annual nutrient mass for stream reaches using SPARROW are made at the catchment scale. Mass fluxes are aggregated to larger scales by connecting stream outlets in one catchment to stream inlets in the adjacent catchment based on a stream network topology and then incorporating in-stream and reservoir losses. Incremental loads and yields (the predicted amount of a constituent leaving a catchment that reflects only those inputs contributed from within the incremental area of that reach), and total loads (the total predicted amount of a constituent reaching a stream reach that reflects the accumulated mass of the constituent contributed by all sources in the total upstream catchments) are estimated for each reach in the model.

In SPARROW model development, a variety of model specifications are evaluated to determine which nutrient sources and landscape characteristics, among those that can be reasonably described for the entire study area, are important in controlling nutrient transport. Parameters that describe the sources and control P fate and transport parameters are identified through a sequential parameter estimation procedure. If nutrient sources are not statistically significant (typically $p < 0.05$), they are combined with other sources in a series of model runs until an acceptable specification is obtained in terms of model fit. Determination of model fitness is made by examining overall root mean square error, $R^2$ values, model-estimated coefficients, variance inflation factors, and residual plots. Coefficients in the model are estimated using nonlinear least squares regression (Schwarz et al., 2006). Once calibrated, SPARROW models can be used in the simulation mode to evaluate how changing source inputs should influence local water-quality conditions and downstream transport (Booth et al., 2011).

The SPARROW model used in this study was calibrated for the upper Midwestern U.S., a region designated as Major River Basin 3 (MRB3) (Robertson and Saad, 2011). Both the GL basin and upper portion of the Mississippi River, Ohio River, and Red River of the North regions were included in the MRB3 version of SPARROW to provide sufficient sites for calibration purposes. We henceforth refer to the SPARROW model developed for the MRB3 region as the MRB3 SPARROW model, but we use the model to provide results only for the GL basin.

The MRB3 SPARROW model was calibrated using 810 P load observation sites with long-term, detrended, average annual loads computed from data extending from 1971 to 2006 (Robertson and Saad, 2011). SPARROW models simulate long-term mean-annual nutrient transport given nutrient inputs similar to a given base year. The MRB3 SPARROW predicts P loads for nutrient inputs similar to 2002 for over 11,000 basins, ranging in size from 45 $km^2$ to 44,000 $km^2$. The 2002 base year was selected to coincide with the most recently available explanatory geospatial (nutrient input) data. Long-term, mean-annual detrended loads incorporate the aggregate effect of hydrologic variability that has occurred over the entire 1971–2006 period. The calibration results indicate that the MRB3 SPARROW model explained 93% of the variance (adjusted $R^2$) in the observed loads. Most predicted values were with 50–200% of the measured values.

The MRB3 SPARROW model has six P sources: point sources, urban land uses, manure from confined animals, manure from unconfined animals, farm fertilizers, and forested land uses (including wetlands), all of which are allocated at the catchment level. The land use-to-water delivery factors in the MRB3 SPARROW model depend on two spatially varying landscape characteristics: soil permeability (compiled from the USDA STATSGO database using methods described by Wolock, 1997) and the percentage of land use underlain by tile drains (compiled from the 1997 National Resource Inventory dataset compiled by the Natural Resource Conservation Service). Nutrient removal in streams is a function of the time of travel, which is based on stream velocity. Average velocity for each reach was estimated from average-annual flow during 1975–2007 from stations throughout the U.S. The inverse of the hydraulic loading is used to describe nutrient removal in reservoirs. Hydraulic loading in reservoirs was calculated as average flow input divided by surface area, for reservoirs included in the National Inventory of Dams (USACE, 2013).

Urban point sources (including public wastewater treatment plants and commercial and industrial effluent) were estimated from data in the USEPA's Permit Compliance System database and supplemented with data obtained directly from state agencies (Robertson and Saad, 2011). P inputs from urban land areas are represented by a combination of urban land use area categories (high, medium, and low density and open space) in each catchment. Urban land use sources are a surrogate for various diffuse P sources including, urban runoff, fertilizers, and septic systems (Robertson and Saad, 2011). P associated with confined and unconfined manure and farm fertilizer application was estimated from county-specific application rates and county-specific animal totals (Ruddy et al., 2006). P inputs from forested areas are estimated from the amount of forest and wetland land use areas in each catchment. A more detailed description of the MRB3 SPARROW model used in this study is given in Robertson and Saad (2011).

### 2.4. Future phosphorus inputs and load calculations

Annual P input predictions (units of kg/year) were made by linking P sources to the LTM UE and UE + BF land use maps for 2010 and 2040. P inputs from urban point sources from the MRB3 SPARROW model were normalized to the population in each catchment to obtain catchment-specific per capita P generation rates (units of kg P/capita/year). These urban point source P generation rates were multiplied by county-level population projections (U.S. Census, 2013) that were disaggregated to catchments. Predictions of diffused inputs from urban areas were made by multiplying the regional diffused urban input rate (units of kg/$km^2$ urban land area/year) associated with the MRB3 SPARROW model by the LTM-predicted urban land use area for a given catchment for 2010 and 2040.

Catchment-specific fertilizer, confined manure and unconfined manure application rates (units of kg P/$km^2$ agricultural land/year) were obtained from the MRB3 SPARROW model. The catchment- and source-specific application rates were then multiplied by the LTM-forecasted areas of agricultural land use in each catchment for 2010 and 2040. This approach assumes that P inputs in new land areas dedicated to biofuel feedstock cultivation in a given catchment occur at the 2010 base year catchment-specific unit rate (kg P/$km^2$ agricultural land/year) for each agricultural source. Predicted P inputs from forested land use areas were made by multiplying the regional forested land use source rate (units of kg/$km^2$/year) from the MRB3 SPARROW model by the amount of LTM-predicted forested land use for 2010 and 2040.

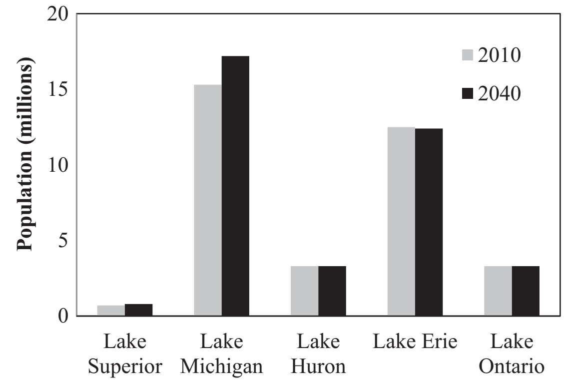


**Fig. 4.** Population in Great Lakes watersheds in 2010 and 2040.

The modified P sources estimated for 2010 and 2040 for the UE and UE + BF scenarios were input into the calibrated MRB3 SPARROW model and P load predictions were made throughout the GL basin.

### 2.5. Vulnerability of watersheds to changes in phosphorus sources

Because the scenarios used here are just one set of many possible population and land use change projections, it is worth describing more generally how watersheds vary in their capacity to retain or export P. We refer to the lack of ability of a catchment to retain P as the catchment vulnerability. Variations in vulnerability are demonstrated by calculating a "total delivery fraction," or TDF, which is based on the key P removal mechanisms in the SPARROW MRB3 model: land-to-water removal fraction and instream and reservoir removal fractions.

The spatial variation in TDF depends on factors related to underlying soil properties, position relative to the outlets to the GL, length of transport, and the presence of surface water reservoirs in a given catchment. Lower permeability soils tend to increase runoff and produce correspondingly greater rates of P migration from the land surface. Tile drains tend to decrease runoff, and, thus decrease delivery of sediment and sediment-bound P to adjacent streams (Zucker and Brown, 1998). The spatial distributions of soil permeability and fraction of land area underlain by tile drains are shown in the Supplementary Material (SM). Catchments with long travel paths and intercepting reservoirs with significant volumes exhibit greater retention of P and, thus, lower TDFs.

## 3. Results

### 3.1. Projected changes in land use, population, and P sources

The predicted population and land use, respectively, across the U.S. portion of the GL basin in 2010–2040 are shown in Figs. 4 and 5(a)–(c). Urban areas are predicted to increase by 41% throughout the GL basin, whereas population will increase only modestly (5%) from 2010 to 2040. This result illustrates the expectation that urban growth will occur primarily as low density residential and commercial development. For the UE scenario, inputs from point sources are expected to increase by 5% from 2010 to 2040, due to a 5% increase in population over the 30-year period,

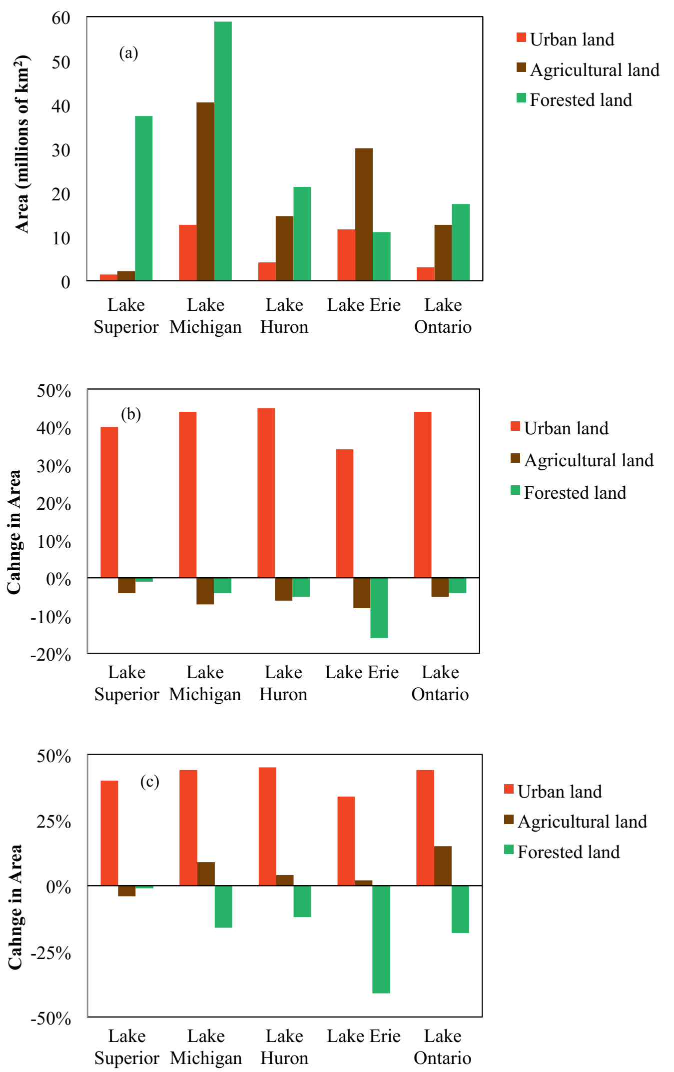


**Fig. 5.** Land use in Great Lakes watersheds in (a) 2010, for (b) urban expansion scenario in 2040 and (c) urban expansion plus biofuel future scenario in 2040.

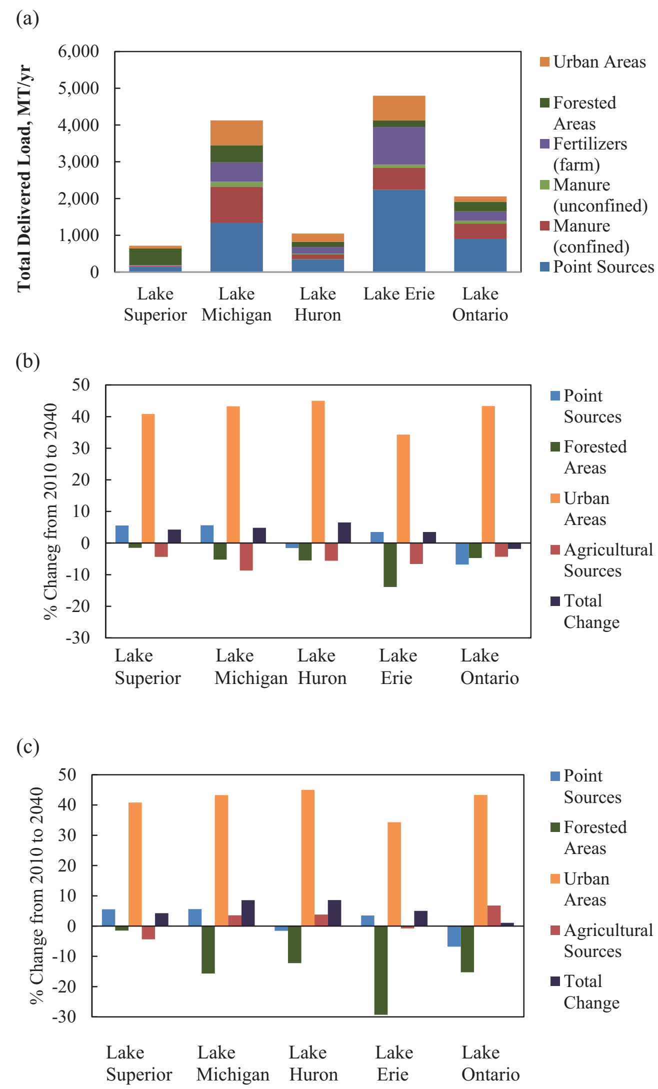


**Fig. 6.** (a) Total annual delivered P load delivered to each Great Lakes for 2010, (b) changes from 2010 to 2040 for urban expansion scenario, and (c) changes from 2010 to 2040 for urban expansion plus biofuel future scenario, subdivided by source category.

and the 41% increase in urban land use from 2010 to 2040 produces a corresponding 41% increase in P from the diffused source input. The predicted P input from agricultural sources (manure confined, manure unconfined, and farm fertilizers) decreases from 2010 to 2040 for the UE scenario by 7%, and inputs from forested land use decrease by 5%, driven by decreases in these land uses. In the UE + BF scenario, the changes in urban land use and sources described above remain the same; however, the amount of P input associated with agricultural sources in 2040 increases by 7% over the whole U.S. portion of the GL basin as compared to 2010, driven by an overall increase in agricultural land use of 14% relative to the UE scenario.

### 3.2. Phosphorus loading to the Great Lakes

The P loadings in the base year for the simulations (2010), compared well with the results from the original SPARROW model results for 2002 P inputs from Robertson and Saad (2011). Differences between the estimated 2010 P loadings and the original SPARROW P loadings were, on average, 2%.

In 2010 (the base year), the U.S. side of the Lake Erie and Michigan watersheds contributed the highest P loads (units of kg/year) to the GL and the Lake Superior watershed contributes the lowest loads (Fig. 6(a)). Fig. 6 also shows that, in general, the highest relative contributions to P loads are from urban point and non-point sources, but agricultural sources are important contributor.

Total annual P delivered to the Lakes (U.S. contribution only) increased from 3.4% and 5.8% from 2010 to 2040 for the UE and UE + BF scenarios, respectively (Fig. 8(b) and (c)). The increase in P loadings for the UE scenario is primarily caused by an increase in urban land (associated with urban diffuse sources), as opposed to increases in population (associated with urban point sources) (Fig. 6(b)). The additional increase in P loadings for the UE + BF scenario in 2040, as expected, is roughly equivalent to the expected increase in agricultural land across the basin of 14% relative to the UE scenario.

### 3.3. Phosphorus yields by HUC8 basin

Fig. 7 shows P delivered yields by HUC8 watershed for 2010 (the base year) and predicted changes in delivered yields for the two scenarios in 2040, respectively. Delivered yields from HUC8 watersheds are the P loads contributed by the watershed to the GL, normalized by watershed area, as opposed to the P load directly emanating from the watershed outlets. Thus, delivered yields indicate

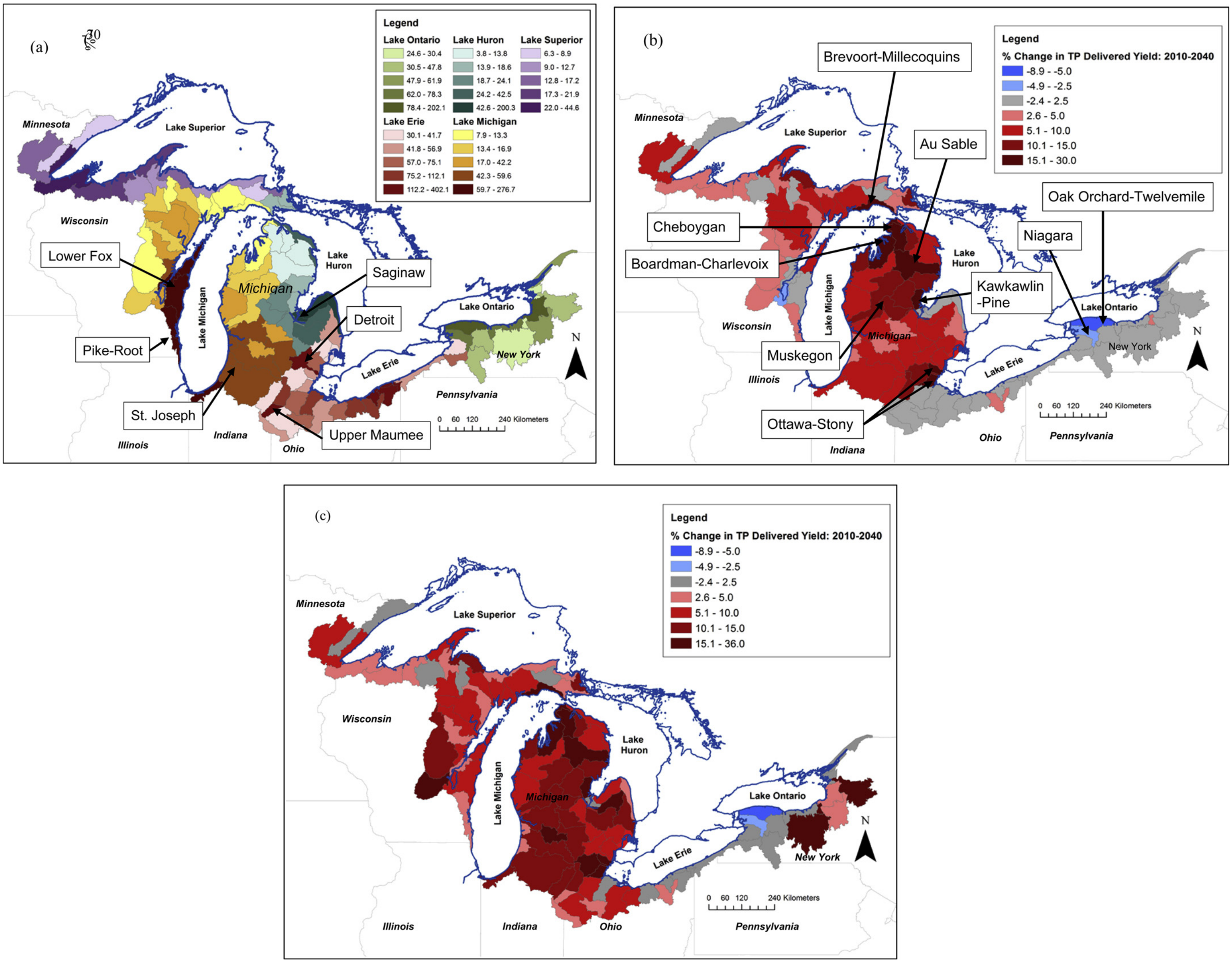


**Fig. 7.** (a) Total delivered P yield in 2010 (kg/km$^2$) by HUC8 watershed, (b) % change in 2040 urban expansion scenario by HUC8 watershed, and (c) % change 2040 urban expansion plus biofuels future scenario by HUC8 watershed. Note that color scheme in (a) is adjusted to normalize for each Great Lakes Basin.

the intensity of a watershed's contribution to GL P loads. In the 2010 base year (Fig. 7(a)), the highest P yields are associated with urban point-source dominated basins, such as the Detroit (Lake Erie), Pike-Root (Lake Michigan), and Saginaw (Lake Huron) and agriculturally dominated basins, such as the St. Joseph and Lower Fox (Lake Michigan) and Upper Maumee (Lake Erie). In the UE scenario, the delivered yields generally increase; however, delivered yields in a few areas decrease (Fig. 7(b)). HUC8s yields in the UE + BF scenario are larger than for the UE scenario, as expected (Fig. 7(c)). Numerical values of loads and yields for each HUC8 basin are given in the SM.

### 3.4. Vulnerability of watersheds to increases in of phosphorus sources

Fig. 8 shows the spatial distribution of the total delivery fraction (TDF) for each of the catchments in the U.S. portion of the GL basin, where lower values indicate greater removal of P and less vulnerability to delivery of the P sources. TDFs vary by about an order of magnitude, indicating that the ability to process P varies greatly across the basin. Most of the higher TDF values occur in areas along the coast of the GL where the watershed areas are narrower and there are shorter travel distances, although there are exceptions in the central and southern portions of the lower peninsula of Michigan and in Ohio.

## 4. Discussion

### 4.1. Changes in lake loadings

The loadings from urban land use will change the most in 2040, for both scenarios (Fig. 8(b) and (c)). Nevertheless, agricultural sources still tend to dominate, providing 35% and 38% of total loadings for the UE and UE + BF scenarios, respectively. Point sources provided the second largest proportion of the loads, with 26% and 29% of total loadings for the UE and UE + BF scenarios, respectively. These results agree with the findings of Robertson and Saad (2011), where P inputs from agricultural sources were found to contribute from 33% to 44% of the total P load over the U.S. portion of the GL basin and point sources contributed from 14% to 44% of total P load.

For the UE scenario, loads associated with point sources decrease or stay the same in three of the five lake drainage areas, because populations are expected to decrease or stay the same in much of the U.S. portion of the GL, with the exception of increases in population growth in the Lake Michigan and Superior drainage areas of 12–15% (Fig. 6(b)). The highest relative

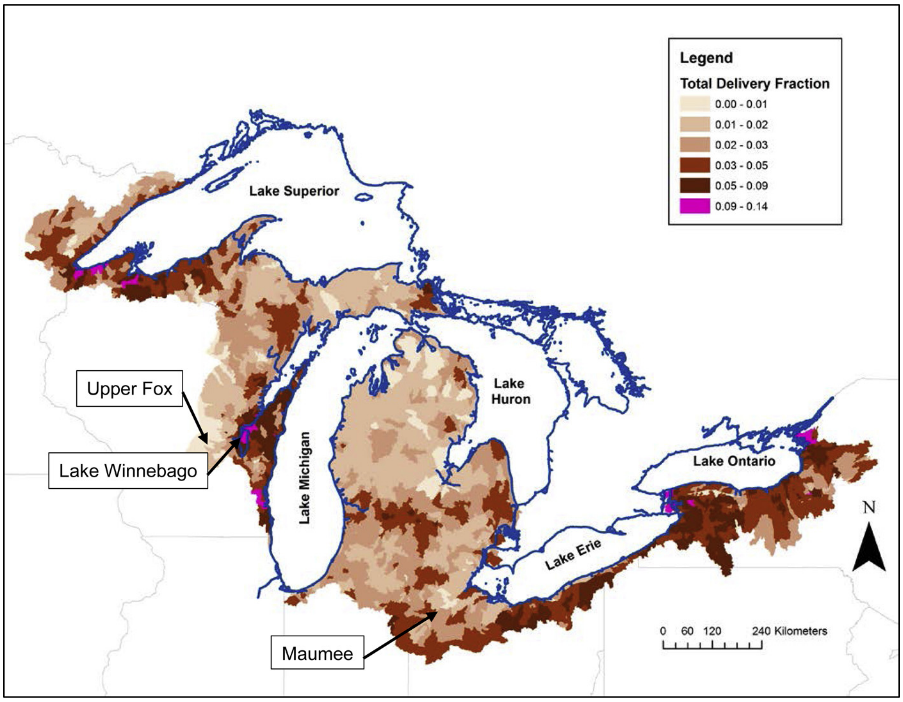


**Fig. 8.** Total delivery fraction for catchments in the US portion of the Great Lakes Basin.

increases and decreases in loadings should occur in Lake Huron and Lake Ontario, respectively. The Lake Ontario drainage area should experience a 7% decrease in point sources, which decrease overall total P loads. Although P loadings from urban areas are projected to increase rather dramatically (increases ranging from 35% to 44% for the five lake drainage areas), this increase has only a small effect on the overall loads because P loadings from urban areas contribute a small fraction of the overall load in most areas. For Lake Ontario, the 42% increase in loading caused by increases in urban area is more than offset by predicted decreases in urban point sources and agricultural land, resulting in an overall decrease in total P loadings for the UE scenario of 1.8% for this lake.

For the UE + BF scenario, the greatest increases in loading relative to the UE scenario occur in Lakes Michigan and Huron, with additional 4.7% and 2.8% increases, respectively. These results reflect the relatively large expected increases in agricultural land in these areas, due to the availability of higher quality agricultural land that would support nearby biofuel production plants. For Lakes Ontario and Erie, the predicted increases in loading for the UE + BF scenario relative to the UE scenario are 3.7% and 2.2%, respectively. The smaller increases for these lakes are a result of less land area available for new agricultural production, given the relatively high fractions of urbanized areas in these lake basins. Lake Superior should experience little change between the UE and UE + BF scenarios because of the lack of expected ethanol production facilities in this lake basin.

An important ecological context for viewing the predicted changes in P loadings is the current performance of each GL watershed with respect to meeting target P loads set in the GLWQA (GLWQA, 2012). We cannot directly compare the loads estimated here to GLWQA target loads, because we do not include load estimates from the Canadian portion of the Great Lakes. However, performance with respect to meeting target loads provides a qualitative context for assessing the vulnerability of the GL to potential increases in P loads.

Dolan and Chapra (2012) quantified annual loads over the years 1994–2008 to determine which lakes have met the GLWQA target loads during this period. They ranked each GL with respect to performance toward meeting target loads as follows (from best to worst performance): Michigan, Huron, Ontario, Erie, and Superior. According to Fig. 8(b) and (c), the GL watersheds can be ranked as follows for projected increases in P loads (from highest to lowest expected increases): Huron, Michigan, Superior, Erie, and Ontario. Combining these two sets of rankings implies that, although the greatest increases in P loads are expected for Lakes Huron and Michigan, these lakes have been the most consistent in meeting target loads and thus may have the greatest buffer for absorbing potential increases in P loads. On the other hand, Superior, the worst performer in terms of meeting target loads according to Dolan and Chapra (2012), is expected to experience relatively large increases in P loads. Target loads for Lake Erie were exceeded 26% of the time during 1994–2008, but it is predicted to have only small increases in loads. For Lake Ontario, while target loads have not been exceeded, the loads have been close to the target for a few years out of the period 1994–2008; however, loads to this Lake are not expected to increase very much.

### 4.2. Phosphorus yields by HUC8 watershed

In the UE scenario, delivered yields generally increased; however, delivered yields in a few areas decreased (Fig. 7(b)). The largest relative increases in delivered yields are expected to occur in Lake Huron and Michigan watersheds (Au Sable, Kawkawlin-Pine, Cheboygan, Boardman-Charlevoix and Brevoort-Millecoquins). These areas tend to be dominated by forested land today, but are expected to experience increases in urban area and population. Delivered yields are expected to decrease the most in the Niagara and Oak Orchard-Twelve-mile HUC8 basins, because of decreases in population and the lack of area available for increases in urban land. HUC8s with the largest increase in the UE + BF scenario relative to the UE scenario are in the western and southeastern part of the Lake Michigan, western Lake Erie, and eastern Lake Ontario basins (Fig. 7(c)). These areas exhibit large increases in load because of the availability of abandoned agricultural land and proximity to potential biofuel plants.

Previous studies examining the impacts of land use change in the Muskegon watershed in western Michigan indicated that P losses from this watershed should increase 3% over a 50-year period (Tang et al., 2005). In the current work, P loads from the Muskegon watershed are expected to increase by 5% and 6% for the UE and UE + BF scenarios, respectively. The difference between the Tang et al. (2005) results and those predicted here are likely due to differences in land use projections and translations of land use categories to P source terms between the current and Tang et al. (2005) studies. In Tang et al. (2005), for example, urban sources appear to be based on land area and not population, which could lead to an under-prediction of P loads from urban areas.

### 4.3. *Vulnerability of watersheds to increases in phosphorus inputs*

In general, TDFs are low in the lower peninsula of Michigan and the eastern portion of the Upper Peninsula of Michigan and northwestern Ohio, where (a) soil permeabilities are high, (b) high fractions of land are underlain by tile drains, and (c) the watershed is relatively far from the GL shoreline (see Fig. 8). TDFs are generally higher along the U.S. shoreline of Lakes Erie and Ontario, the western shore of Lake Michigan and the western portion of the Upper Peninsula of Michigan. Most of these catchments are relatively close to the GL, tending to increase TDFs; however, a few of these catchments have high soil permeabilities or high fractions of land area underlain by tile drains, which decreases TDFs in these catchments.

Catchments in central Wisconsin uniformly have low TDFs because these catchments drain to the Winnebago Pool lakes, which are highly effective at removing P, given its large volume. The mostly low TDFs in the Maumee River catchments (southeastern Michigan and northwestern Ohio) and the Upper Fox River (central Wisconsin) are of particular importance. P sources are relatively high in magnitude in these areas, due to intensive agriculture, in the present and, according to the UE + BF scenario, increasingly so in the future. The lower TDFs in these areas imply that increases in P sources will be buffered in these areas; however, the quality of the intercepting reservoirs may be in jeopardy.

### 4.4. *Limitations of the approach*

The modeling approach used in this study assumes that watershed hydrology will remain the same as that used in the MRB3 SPARROW model, which may not be valid given the potential for the forecasted land use changes and climate change to modify the hydrology of the area. Land use change alone could influence the magnitude of streamflows; for example, increased urbanization would be expected to result in higher peak stream discharges, which could, in turn, produce greater P loads. For example, a study of the Muskegon River, Michigan, watershed showed that over the next 100 years, changes in land use would result in increases in median daily P loads could increases of 4–39%, for scenarios with minimal and aggressive levels of urban expansion, respectively (Wiley et al., 2010). The predictions presented here also assume that practices related to urban and agricultural generation of P will remain static over the prediction period. Improvements in wastewater treatment and stormwater management practices could also result in lower magnitudes for point and nonpoint urban source terms, respectively.

In addition, we have not included potential changes in P loads due to future climate change. Most studies indicate climate change could result in changes in precipitation in the GL region that could affect streamflows. Increased precipitation could produce increased high flow events, which in turn are likely to generate greater P load (Kunkel et al., 1999: Trefry et al., 2005; Hubbard et al., 2011). Increased air temperatures, however, will increase evapotranspiration and decrease streamflow. It is likely that areas that already have precipitation frequency distributions that are skewed toward high flow events will be affected the most by increases in precipitation. In Lake Michigan watersheds, both mean annual flow and peak flows are projected to increase (Cherkauer and Sinha, 2009). Increases in P loads in these watersheds, then, could be underestimated. Barlage et al. (2002) predicted changes in runoff due to scenarios of land use and climate change for a watershed in southeastern lower Michigan. Their results show that roughly 60% of the increases in runoff will be due to forecasted climate change with the remainder or runoff increase due to land use change.

USEPA (2013) found that P loads from the Maumee HUC8 basin in the western Lake Erie basin should change from −12% to +50%, depending on the climate and land use scenario, with a median increase of 25%. These changes compare to increase of 1–7% for the UE and UE + BF scenarios, respectively, in the current work. The primary difference between the two studies is that USEPA (2013) includes effects of climate change. Average streamflows are predicted by USEPA (2013) to change by roughly the same fractions as the P loads, due to climate change, implying that climate change could be a more important driver for changes in P loads than land use change.

Predictions of inputs from agricultural sources are subject to several underlying assumptions. It has been assumed that agricultural practices that affect the transport of P introduced to the land surface into adjacent streams will not change. Discussions of cultivation, fertilizer and manure application, agricultural residues, and other best management practices as they relate to P loads in the GL are continuing (Great Lakes Commission 2012). Bosch et al. (2013) reported that implementation of best management agricultural practices (BMPS, i.e. cover crops, filter strips, and no-till cultivation) in the western Lake Erie basin could reduce P loads by 5–16%, but it is not clear whether the same results would occur for biofuel crop cultivation.

In addition, the cropping mix related to biofuel feedstock production may affect P source generation, since P loads from agricultural land uses are highly dependent on the crop type and cultivation practices. Recent work examining patterns of agricultural change in response to biofuel demand indicates that increases in corn production are occurring with a decrease in the amount of corn rotation with soybeans (Plourde et al., 2013). The Energy Independence Security Act of 2007 set Renewable Fuel Standards to the year 2022 requiring that more than 50% of the nation's ethanol be produced from cellulosic (non-food based) stocks. However, cellulosic processing plants have not, in general, are not prevalent in the U.S. (Tyner, 2010).

The predicted increases in P loads for either scenario examined in this study may seem relatively small, on average, compared to uncertainty in MRB3 SPARROW model predictions. However, these prediction errors represent the noise in our relationships, not the overall signal described by the model. Thus, we are confident in the model's ability to describe the best predicted change in the loads, although the uncertainty around the best estimated load for any specific catchment may be on the order of the uncertainty observed in the calibration results described by Robertson and Saad (2011).

## 5. Concluding implications

In closing, we see that this work can inform policy makers as to how and where to emphasize policy responses in anticipation of future increases in P loads. First, the predictions indicate that the greatest increases in P loads are likely to be associated with expansion of urban areas, even in the case where significant agricultural expansion occurs due to increases in biofuel feedstock cultivation.

Second, we have identified watersheds where sources of P are most likely to contribute to increased loads to the GL, due to predicted urban and agricultural expansion. Finally, we have identified watersheds that are most vulnerable to increases in loads to the GL, exclusive of the predicted scenarios.

## Supplementary materials

The supplementary material includes descriptions and maps of input sources for P source categories figures indicating incremental yields for 2010 and the percentage change from 2010 to 2040 for UE and UE + BF, a detailed description of results for a model lake (e.g., Lake Erie), rankings of HUC8s based on total P yield and load to the GL; output from the SPARROW MRB3 model for 2010 and 2040 including loads and yields for each GL, and loads and yields for each tributary greater than 150 $km^2$ ranked by their relative contribution to each GL.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2014.01.016.

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