Land Use Model Integrating Agriculture and the Environment (LUMINATE): Linkages between Agricultural Land Use, Local Water Quality and Hypoxic Concerns in the Gulf of Mexico Basin

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LAND USE MODEL INTEGRATING AGRICULTURE AND THE ENVIRONMENT (LUMINATE):
LINKAGES BETWEEN AGRICULTURAL LAND USE, LOCAL WATER QUALITY AND HYPOXIC CONCERNS IN THE GULF OF MEXICO BASIN

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Abstract

In this paper, we discuss the importance of developing integrated assessment models to support the design and implementation of policies to address water quality problems associated with agricultural pollution. We describe a new modeling system, LUMINATE, which links land use decisions made at the field scale in the Upper Mississippi, Ohio, and Tennessee basins through both environmental and hydrologic components to downstream water quality effects and hypoxia in the Gulf of Mexico. This modeling system can be used to analyze detailed policy scenarios identifying the costs of the policies and their resulting benefits for improved local and regional water quality. We demonstrate the model’s capabilities with a simple scenario where cover crops are incentivized with green payments over a large expanse of the watershed.
Introduction

Water quality problems remain ubiquitous around the world and in many locations are growing in severity. Nutrient enrichment of freshwater and coastal areas from a variety of human activities including agricultural runoff, sewage, and industrial sources is the most prevalent type of water quality problem (http://www.un.org/waterforlifedecade/quality.shtml). The delivery of nutrients, primarily nitrogen (N) and phosphorus (P), into waterways accelerates normal plant growth in a process called eutrophication. Eutrophication of water bodies results in a range of lost ecosystem services (Tilman et al, 2001; Chislock, et al. 2013) whose values are increasingly understood and monetized (Barbier, 2012; Polasky and Segerson, 2009). For example, eutrophication problems in local freshwater systems such as lakes and streams can include excess algae growth, changes in water clarity, odor, and toxic algae blooms. In addition to these local effects, excess nutrients can cause detrimental effects far downstream.

A striking example of large-scale eutrophication problems with both detrimental local water quality effects and major downstream problems occurs in the central United States. Two major watersheds, the Upper Mississippi River basin (UMRB) and Ohio-Tennessee River basin (OTRB), each exhibit significant local water quality problems (http://ofmpub.epa.gov/waters10/attains_nation_cy.control), and contribute significant nutrient loadings to the Northern Gulf of Mexico where eutrophication results in an annual hypoxic zone (EPA-SAB, 2007; Rabotyagov et al., 2014). Oxygen-depleted (dead) zones have increased exponentially since the 1960s and now impact over 400 coastal marine systems (Conley et al, 2011; Diaz and Rosenberg, 2008). Since 1985, Rabalais and others have documented the annual extent of the seasonal hypoxic zone that forms in the Northern Gulf of Mexico (Rabalais et al., 2010; Turner et al., 2006). Figure 1 shows the size and location of the watersheds.
The current agricultural land use pattern in the watershed has resulted from the simultaneous decisions of over half a million individual landowners and agricultural producers over decades. These decisions have been influenced by crop profitability dictated in turn by economic conditions including commodity and energy policy. When scaled up to the basin level, the result has been a highly productive agricultural region, but as noted above, there has been significant degradation to water quality and other ecosystem services.

Federal and state governments are actively looking for solutions and a number of conservation actions that can reduce nutrient loss from agriculture are available. However, to be effective (and even more so in order to be cost effective), the cumulative and nonlinear effects that occur when abatement activities adopted on individual farms are scaled up to the watershed level need to be incorporated. For example, if multiple contiguous landowners install conservation practices along a river, this may have significantly more impact on downstream water quality than if the same number install those practices at noncontiguous locations. Likewise, nutrient loadings in some locations in the watershed have a much lower possibility of being transported to the Gulf than others depending on the features of the landscape and hydrology. It is further important to realize that nutrient fate and transport is not in general an exogenous physical process, but is in fact endogenous to water quality policy (for example, when a reconstructed wetland effectively traps and removes nutrients from upstream sources). Equally important is to recognize that the costs of adopting abatement actions vary by location with soil characteristics, farming practices, weather patterns, and a host of other location-specific features. An integrated modeling system that incorporates these nonlinearities, scale effects, and cost variability will be essential for good public policy.
In this paper, we describe the development and implementation of an integrated assessment model for this large region of the central United States. Our coupled natural and human system captures the key nonlinearities in spatial processes associated with scaling up the impacts of individual decision making at the single agricultural field scale to the impact on local watersheds and the downstream hypoxic conditions. We begin with a brief literature review of integrated land use and water quality assessments. After describing an overview of the modeling system, we describe the components in more detail. We then present the results of a simple, but detailed land use scenario where the effects of large-scale placement of cover crops across the watershed are simulated. This simple scenario is used to demonstrate the potential for the modeling system to inform policy as the simulated output includes predictions of the change in water quality throughout the large watersheds (including the local and downstream impacts), the impact on marine eutrophication, as well as the costs of adopting these practices. The results presented here highlight the value of such a modeling system for policy design and implementation. In the final section, next steps and additional discussion of the potential role of integrated assessment models are described.

**Literature Review**

In general terms, the literature related to Northern Gulf of Mexico hypoxia and water quality problems in the watershed fall into two broad categories: (a) studies that focus entirely on the bio-physical aspects of the processes contributing to the northern Gulf of Mexico hypoxia, and (b) studies that attempt to integrate the socio-economic and the bio-physical aspects of the water quality processes. In the first category, there are studies that focus on the modelling of Northern Gulf of Mexico hypoxia, but do not link to specific land use management strategies.
(Justic et al., 2002; Scavia et al., 2003; Turner et al., 2006; Justic et al., 2007), studies that focus on estimating the nutrient loadings that ultimately reach the Gulf, but cannot perform scenarios relating specific land use changes to the hypoxic zone (Burkart and James, 1991; Donner et al., 2002; Booth and Campbell, 2007; and Alexander et al. 2008; Broussard and Turner, 2009), and studies that estimate the nutrient loading and at the same time consider the impact of different land use scenarios (Johnes and Hearhwaite, 1998; White et al., 2014).

The “integrating” modelling literature considers the impact of different land use scenarios on water quality by focusing on smaller watersheds rather than large scale. These studies, although incomplete in one or more dimensions and not providing any direct linkage to Gulf of Mexico hypoxia, offer valuable insights and alternative policy options that have the potential to reduce the hypoxia’s size. In some cases, the complex relationship between runoff leaving the field and its impact on the overall water quality is simplified by estimating different proxy alternatives: delivery coefficients (Khanna et al., 2003) or point systems (Rabotyagov, Valcu and Kling, 2013). The ultimate goal of these studies is to identify the cost-effective land use changes and to design the optimal economic incentives to reduce the runoff in the landscapes dominated by agriculture.

Similarly, within the “integrating” literature, we can further identify several categories: studies that provide extensive reviews of the programs that have been implemented, studies that compare the cost-effectiveness of different land use scenarios, studies that consider the optimal placement of the conservation practices, and studies that considers the impact of different policies (i.e., biofuel crop production) on water quality.

Ribaudo et al. (2001) compare the cost effectiveness of a fertilizer standard and wetland restorations as N reduction methods in the Mississippi basin. Doering et al. (2001) provide an
economic analysis for reducing N on a large scale, but they rely on aggregate data that is not watershed based. Greenhalgh and Sauer (2003) present a comprehensive assessment of different cost-effective policy options to alleviate hypoxia, but with a focus on the local water quality issues. Wu and Tanaka (2005) estimate the costs of adopting three different conservation policies and a tax on the use of fertilizer in the UMRB. Secchi et al. (2007) outline a methodology to assess the economics costs and water quality benefits by considering a number of hypothetical land use scenarios for thirteen watersheds in Iowa, one of the states with the highest contributions to the hypoxia. Jenkins et al. (2010) evaluate the benefits of wetland restoration in the southern part of the Mississippi corridor.

Rabotyagov et al. (2010) integrate a watershed-based model with cost data and develop, via evolutionary algorithms, a tradeoff frontier for the UMRB specifying the least cost of achieving different level of N and P reductions. For the same large watershed, Secchi et al. (2011) assess the water quality changes in the context of an increase in the corn acreage due to an ethanol policy.

**Description of Study Regions**

The UMRB drains 492,000 km² including large parts of Illinois, Iowa, Minnesota, Missouri, and Wisconsin, from Lake Itasca in Minnesota to just north of Cairo, Illinois, above the confluence with the Ohio River (Figure 1). The area is referred to as Region 07 by the U.S. Geological Survey (USGS) at a 2-digit watershed scale and is further comprised of 131 USGS 8-digit watersheds and 5,729 USGS 12-digit subbasins (USGS, 2012). The average annual UMRB rainfall within the last 4 decades was 900 mm, ranging from 600 to 1,200 mm across the basin with values generally decreasing from east to west. Cropland consists mainly of corn-soybean
rotations and occupies almost 50% of the total UMRB area, with the majority of the land area consisting of slopes less than 5%.

The Ohio-Tennessee river basin covers about 528,000 km² including large portions of seven states as shown in Figure 1. The OTRB is comprised of 152 8-digit watersheds and 6,350 12-digit subwatersheds. The OTRB region received nearly 1,200 mm/y of average annual rainfall during the last 40 years. About half of the land cover in this basin is forested, with the majority of the remaining area planted in crops (20%) or managed as permanent pasture/hay (15%). Corn, soybean, and wheat are the major crops grown (Santhi et al., 2014). Compared to the UMRB, the OTRB’s slopes are much steeper, especially across the forested Tennessee basin; however, cropland is mostly concentrated in the Northwestern part, which is characterized by mild topography.

According to USEPA SAB (2007), 43% of the nitrate load and 26% of the total phosphorus (P) load delivered to the Gulf of Mexico came from the UMRB from 2001 to 2005, in spite of the fact that the UMRB drains only 15% of the total Gulf of Mexico drainage area. The mean annual in-stream UMRB total nitrogen (N, nitrate plus organic nitrogen) and P loads measured at Grafton, Illinois (Figure 2) are 500,000 t/y and 30,000 t/y, respectively (USGS, 2013). Likewise, the OTRB exports roughly 500,000 t of N annually to the main Mississippi River channel, with close to 67% in the form of nitrate. The annual average phosphorus loads measured at the OTRB outlet equal 48,000 t/y (USGS, 2013).

**Overview of the LUMINATE System**

Current water quality conditions in the UMRB and OTRB and the delivery of nutrients from these watersheds to the Gulf of Mexico results from the decisions of thousands of agricultural
producers concerning crop choice, conservation practices and management choices. These decisions depend in turn on many factors including soil type, climate, expected market prices as well as policy variables such as subsidy levels. Figure 3 describes the basic components and model integration of the LUMINATE modeling system which is designed to capture the key features of this complex interaction between human decision making, land uses across this broad landscape, and the resulting effects on water quality in the upstream watersheds as well as the Gulf of Mexico. As noted in the central top of the schematic, the primary purpose of the modeling system is to be able to undertake scenarios associated with changes in policy variables, weather conditions, and market forces. The two key “upstream” water quality models of this integrated system are identified in the box labeled “SWAT UMRB and OTRB Models,” which are fed and parameterized by a range of data inputs. The Soil and Water Assessment Tool (SWAT), a watershed-scale water quality model (Arnold et al., 1998; Arnold and Forher, 2005; Gassman et al., 2007) forms the core of the watershed water quality component of the modeling system proposed here and was used to construct the specific UMRB and OTRB models. As described below, the SWAT model of the region was developed to simulate a greater range of cropping systems and management practices.

Data and modeling representing economic drivers of land use are used in conjunction with scenario design to determine landscape configurations which are then fed into the SWAT modeling system. The output of this modeling is a spatially explicit prediction of nutrient loads and other water quality indicators throughout the basin. The final key model component of the overall modeling system is the hypoxic zone model, represented in the lower central box.

An important feature of the modeling system built here is the ability to interface the model with an optimization heuristic (evolutionary algorithm) for scenarios in which optimal landscape
configurations to achieve a given environmental (or cost) goal are desired. While not necessary for running simple scenarios (such as the one presented in this paper), evolutionary algorithms are powerful tools for identifying and analyzing tradeoffs across a large range of cost and environmental objectives (see Vrugt and Robinson, 2007; Rabotyagov et al., 2010) while employing the full suite of biophysical models, allowing for consistency of assumptions and a full coupling of cost effective policy and natural science modeling. Regardless of whether the evolutionary algorithm is employed, the modeling system is also useful in evaluating specific policy scenarios.

Previous SWAT UMRB and OTRB applications relied on delineation approaches in which the subwatershed boundaries were aligned with 8-digit watershed boundaries (e.g., Rabotyagov et al., 2010a; Srinivasan et al., 2010; Secchi et al., 2011; Santhi et al., 2014). However, a greatly refined delineation scheme has been incorporated into the UMRB and OTRB SWAT models used in LUMINATE, which consist of using subwatershed boundaries that are coincident with the much smaller USGS 12-digit watersheds. This detailed subwatershed schematization allows for improved linkages to climatic inputs, better representation of stream routing processes (and thus the nonlinearities and potential endogeneities in nutrient fate and transport), and improved targeting of management practices and cropping systems on agricultural landscapes.

**SWAT Model Description and Water Quality Modeling System**

SWAT is a conceptual, long-term continuous watershed-scale simulation model that is usually executed on a daily time step. Key components of the model include hydrology, plant growth, sediment loss and transport, nutrient transport and transformation, pesticide fate and transport,
and effects of management practices. Typical applications of SWAT involve delineation of a watershed into subwatersheds, which are then further subdivided into subareas consisting of homogeneous land use, soil types, and slope classes that are called hydrologic response units (HRUs). However, a “dominant HRU approach” can also be used in which just the dominant soil, land use and topography are used to define the complete characteristics of a given subwatershed, resulting in the subwatershed being equivalent to a single HRU. Flow and pollutant losses are generated at the HRU level in SWAT, aggregated to the subwatershed level, and then routed through the stream system to the simulated watershed outlet. SWAT has been successfully applied in extensive applications worldwide for a wide range of watershed scales and environmental conditions (Gassman et al. 2007; 2014; Douglas-Mankin et al., 2010; Tuppad et al., 2011).

Topographic, soil, land use, climate, management, and other key data are required for assembling and executing a SWAT simulation (Table 1). These data layers were assembled for the UMRB and OTRB models, and then overlaid on the subwatersheds for both regions, using ArcGIS (version 10.1) SWAT (ArcSWAT) interface (SWAT, 2013). The dominant HRU approach described above was used for both regions such that each 12-digit subwatershed was equivalent to an HRU. Topographic characteristics such as slope and slope length were incorporated for each region using a 30 m digital elevation model (DEM) (USGS, 2013). Crop rotations and other land use were incorporated by utilizing three years (2008 to 2010) of the parcel-level USDA-NASS Cropland Data Layer (CDL) datasets (USDA-NASS 2012) with the 2001 National Land Cover Data (NLCD) (USGS, 2012b), similar to the approach used by Srinivasan et al. (2010). Dominant soil types and soil layer characteristics were determined by
using 1:250,000 State Soil Geographic (STATSGO) soil data (USDA-NRCS, 2012b). Major reservoirs are accounted for in both models based on data obtained from USACE (2013).

Management practices accounted for in the SWAT models (Table 1) included subsurface tile drains, tillage practices, fertilizer and manure application rates, and indirect accounting of other conservation practices such as terraces and contouring due to a lack of spatial estimates of such practices. The assignment of subsurface drainage tiles, which are key conduits of nitrate to surface waters, to specific subwatersheds was based on spatial distributions estimated by Sugg (2007) and soil/landscape properties. Tillage practices were imputed to specific subwatersheds by disaggregating distributions of tillage practices, which were compiled at the 8-digit watershed level by Baker (2011), to the 12-digit watershed level (while maintaining the overall 8-digit distributions to the extent possible). Nutrients applied to cropland ranged between 117-156 kg/ha N and 25-34 kg/ha P, respectively, with N applied only to corn, using state-level annual averages reported by IPNI (2010). SWAT auto-fertilization routine was used to simulate nutrient inputs to hay and pastureland. Point sources of N and P have also been inserted to the model based on data compiled by the U.S. Geological Survey (USGS) (Maupin and Ivahnenko, 2011; Robertson, 2013).

The UMRB and OTRB SWAT models were calibrated and validated for the 1981 to 2010 time period based on measured river flows, sediments, and N and P loads at several locations along the rivers (Figure 3). Additional details about the development of the required data layers and management inputs for the UMRB and OTRB SWAT models as well as the calibration processes are described in Panagopoulos et al. (2014a; b).

**Hypoxia Model, Specification, and Coefficients**

A part of the integrated assessment system is an empirical relationship between spring N and P riverine loads and the areal extent of Gulf hypoxia (similar to the model described in
Ecological theory suggests that the extent of hypoxia should be a function of nutrient inputs. Thus, the 2008 hypoxia Action plan recommends a dual nitrogen and phosphorus reduction strategy. To date, statistical evidence on the impact of multiple nutrients on the size of the hypoxic zone has not been unanimous. In fact, debate on the factors responsible for the severity of the hypoxic zone goes back as far as Wiseman et al. (1997), who first observed a relationship between Mississippi streamflow and the area of hypoxia. Several studies have made use of the Streeter-Phelps model, which is typically used to predict the impacts of point source loads on oxygen concentrations downstream, with a focus on the role of N. Examples include Scavia et al. (2003), Scavia and Donnelly (2007), Liu et al. (2010), and Scavia et al. (2013). The empirical corroboration of the importance of multiple nutrients has been elusive. Hypoxia formation is a complex, dynamic, and heterogeneous process, potentially subject to impacts of winds, ocean currents, and disruptive weather events (storms and hurricanes). Further, the history of nutrient enrichment of the Gulf may matter. Turner et al. (2006) speak of “ecosystem memory,” where system attributes are carried from one year to the next, “as would happen if organic matter accumulating in one year was metabolized over several years.”

Previous statistical models include Turner et al. (2006), who postulated that nitrogen, phosphorus, and silicate, as well as lags in nutrient inputs as short as one month before the hypoxia size measurement in July and as long as three years prior would be significant in explaining hypoxic area variability. They found that nitrogen loads, as well as phosphorus loads, lagged one or two months before July were significant. However, the best model in their study was one relating May N and a time trend to the size of hypoxia (explaining 82% of observed variation).

Greene et al. (2009) used a stepwise regression (both backward and forward selection) procedure to choose the month of nitrogen and phosphorus concentrations and river flows to be
included in the model. In the best models reported, May nitrogen concentrations, May flows, and February phosphorus concentrations were reported as significant. They also report that a post-1993 dummy variable was significant, and interpret potential evidence of a regime shift in the system (and the inclusion of the dummy made the impact of phosphorus non-significant).

Finally, Forrest et al. (2012) explored the power set of 11 regressors using Bayesian Information Criterion for model selection. Their primary focus was on identifying the impacts of nitrogen concentrations, a time trend (or a changepoint), and wind patterns (postulated to affect hypoxia formation). They, too, found evidence of positive impact of nitrogen, of a linear time trend, or a post-1993 regime shift.

We build upon the existing work and estimate the area of the hypoxic zone using simple production function estimation methods and attempt to account for the possibility of multi-year lags, multiple nutrients, possible cumulative impacts, and the time-series structure of the data. Nutrient loading data comes from the official USGS estimates (as described in Aulenbach et al., 2007). As postulated in much of the existing literature, the areal extent of hypoxia (in km²) depends on current and past loadings of nitrogen \(N_{t-i}\) (as \(\log_{10}\) transform of May USGS estimates of mainstem Mississippi River loads) and current loading of phosphorus \(P_t\) (\(\log_{10}\) transform of May USGS estimates). We test for the cumulative effects of nitrogen and phosphorus by adding five-year cumulative loadings to the model. We explore the effect of hurricanes and unusual current conditions and their interactions with nitrogen and phosphorus. Specifically, we estimate:
\[ \text{HypoxicZone}_t \\
= \beta_{\text{intercept}} + \beta_{\text{hurricane}} \text{Hurricane}_t + \beta_{\text{currentCurrent}}_t \\
+ \beta_{\text{hurrsN}} \text{Hurricane}_t * \log(10(\text{Nstock5}_t)) + \beta_{\text{hurrsP}} \text{Hurricane}_t \\
* \log(10(\text{Pstock5}_t)) + \beta_N P_t \\
+ \sum_{i=0}^{5} \beta_{iN} N_{t-i} + \beta_{\text{Nstock5}} \text{Nstock5}_t + \beta_{\text{Pstock5}} \text{Pstock5}_t + \epsilon_t \]

where \(N_t = \log(10(\text{May N load at time } t))\) and \(P_t = \log(10(\text{May TP load at time } t))\), and \(\text{Nstock5}_t = \sum_{i=0}^{4} \text{USGS_May}_N \text{N}_{t-i}\) and \(\text{Pstock5}_t = \sum_{i=0}^{4} \text{USGS_May}_P \text{P}_{t-i}\). We estimate the model using hypoxia size measurements from 1985 to 2010 (excluding 1989 when lack of funding precluded data collection), and use the 2011–2013 observations to assess model performance. Estimating separate coefficients for each lagged nutrient values using the available 25 observations would quickly use up degrees of freedom, so a polynomial distributed lag model (Greene, 2003), which constrains the lagged regressors’ parameters to lie on a polynomial, was used. While higher-degree polynomials were tested, a linear form of the lag distribution was used. Since the hypoxia area data are collected over time, an autoregressive error model was estimated. That is, the error term is assumed to follow \(\epsilon_t = u_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2}\), where \(u_t \sim N(0, \sigma^2)\).\(^1\)

An additional criterion for model specification different from the specification reported in Rabotyagov et al. (2014) is the ability of the SWAT modeling framework to simulate the inputs to the statistical hypoxia model. SWAT simulations do not include silicates, and, given that the impact of silicates is was estimated to be small, silicates are not included in the specification.

\(^1\) Longer autoregressive lags in the error term were explored as well but no significant evidence for them was found. In addition, we tested and did not find significant evidence of heteroskedasticity.
Meteorological variables considered by Forrest et al. (2012), including “wind power” and the Sea Surface Temperature anomalies, are only available through 2010, and given that they are outside of the nutrient management control efforts, they are implicitly left in the residual, although their effects have been reported in Rabotyagov et al. (2014). Visually, the structural part of dependence of hypoxia on single-year May N and P values can be shown as a “hypoxia production function” (Figure 4).

**Cover Crop Scenario**

Winter cover crops, including rye, oats, winter wheat or other close-grown crops, are increasingly being used in the Corn Belt region to maintain and improve the quality of soil resources, and mitigate export of sediment and nutrients from cropland landscapes (Kaspar et al., 2012; Kaspar and Singer, 2011; Kovar et al., 2011; Tonitto et al., 2006). In this study, the cover crop scenario consisted of planting rye within the typical two-year rotations of corn and soybean or continuous corn, in which the rye cover crop was planted in the fall after corn or soybean harvest and then harvested shortly before planting of the following row crop in the spring.

The scenario was applied to virtually all of the cropland in both regions (slopes <5%) that included tile-drained areas on flatter landscapes. These tile-drained landscapes are primary source areas of exported nitrate-nitrogen, which is a key water quality problem in regional stream systems (Jha et al., 2010; Schilling and Wolter, 2008; Secchi et al., 2010) and also a key contributor to the pervasive Gulf hypoxic zone (Rabotyagov et al., 2014; EPA SAB, 2007; Turner et al., 2006). The implementation of the cover crop scenario provides an assessment of how much such widespread adoption of the practice can reduce nitrate losses from these landscapes as well as the impact of the practice on overall reduction of sediment, N and P. The
cover crop scenario was implemented within the same 30-year period that the baseline testing was performed for, with all other model parameters (climate, soil, and other management practices) unchanged.

**Results and Discussion**

Table 2 summarizes the SWAT results of the baseline and the cover crop implementation for both the UMRB and OTRB basins. The third row of the table indicates the area of cover crop implementation in the two basins, showing the large extent of affected agricultural areas in the Corn Belt. The cover crop within the traditional rotations resulted in reduced sediment, nitrate, N and P. As shown in Table 2, the reduction of all pollutants was greater in the UMRB due to the larger agricultural area where cover crops were established. Reductions were on the level of 20-25% for N. The estimated P reduction was similar to the predicted sediment reduction due to the fact that phosphorus transport is closely tied to sediment movement.

Table 3 summarizes the annual pollutant loads from both basins that enter the Mississippi River and clearly show that all of the annual pollutant loads decreased by about 20% due to the widespread adoption of cover crops. Table 4 further shows annual N and P loading reductions on a unit land area basis. The N loadings were reduced by 8.38 kg/ha and 13.65 kg/ha in the UMRB and OTRB, respectively, while the P loadings were reduced by 0.39 kg/ha in the UMRB and 0.72 kg/ha in the OTRB. These impacts are comparable in relative magnitude with the overall N and P reductions reported in studies performed for the U.S. Department of Agriculture Conservation Effects Assessment Project (CEAP) for the UMRB and OTRB. However, our

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2 The kg per ha values represent the average reductions.

3 Depending on the scenario, the N reductions for the UMRB range between 6.5% and 42% reductions, (USDA-NRCS, 2012b), while for the OTRB they range between 12% and 50%. (USDA-NRCS, 2011)
cover crops scenario differs from the CEAP scenarios in several aspects: (a) we consider a
significantly larger treatment area, (b) cover crops were not simulated in all of the CEAP
scenarios, and (c) cover crops are just one of several conservation practices considered in the
CEAP assessments. While a direct confirmation is not possible, these relative comparisons
provide further support for our results.4

To provide some context for these analysis, assume that the costs of cover crops range from
$61.8/ha to $86.6/ha ($25 to $35 per acre), then we estimate that the cost of reducing a kilogram of
N ranges between $7.39 to $10.34 for UMRB and between $4.53 to $6.35 for OTRB (Table 4).5
The equivalent costs of reducing a kilogram (pound) of N reported by the CEAP assessments range
between $6.6 and $39.6 ($2.66 to $16 per pound) for the UMRB and $9.65 and $26.9 ($3.9 to
$10.9 per pound) for the OTRB. The total estimated costs for this scenario range between $1.4
billion to $1.9 billion for the UMRB, and between $620 to $870 million for the OTRB.

**Hypoxia model results**

The estimated statistical relationship between contemporaneous, lagged, and stock levels of
nutrients performs well relative to historical data and was able to predict the areal extent of the
zone for 2011 and 2012 with greater precision than existing empirical models utilized by USGS
to create annual forecasts (Figure 5).6

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4The CEAP reports consider five conservation scenarios: the treatment of critically undertreated acres (with a
high need for conservation treatment) with water erosion control practices only, water erosion practices only,
but now applied to a larger share of cropland (with high or moderate need for conservation treatment, nutrient
management practices simulated in addition to water erosion control practices on acres with high conservation
treatment need, and nutrient management practices in addition to erosion control practices on acres with high or
moderate conservation treatment need. The percentage area for high and moderate need is 60% in the UMRB,
and 70% in the OTRB. Cover crops is considered as a water erosion conservation practice.
5 A similar analysis can be made for the cost of reducing a kilogram of P.
6 USGS publishes annual forecasts of the hypoxic zone after May nutrient estimates are released by USGS and
before the Gulf hypoxia measurements are made later in the summer. The empirical relationship in LUMINATE
was used to compare its out-of-sample predictions for 2011, 2012, and 2013 hypoxia with the forecasts released
Table 1 presents the coefficient estimates and fit statistics for the model. We find that the areal extent of hypoxia depends on multiple nutrients in fairly complex ways. As postulated in much of the existing literature, we do find that the areal extent of hypoxia (in km²) depends on contemporaneous spring nitrogen (May nitrogen). However, we also find that that spring nitrogen affects the hypoxia size with an up to a five-year lag, but the multiplicative cumulative effect is moderated somewhat (as shown by the negative coefficient on the five-year sum of May N loadings). While nitrogen affects the size of hypoxia as both a flow and a stock, phosphorus (May P) affects the size of hypoxia as a stock ($P_{stock5}$ significant and positive, $\log P$ not significant). Significant impact of lagged nutrients and the significance of nutrient stocks is consistent with the proposed “ecosystem memory” conjecture for Gulf hypoxia (Turner et al., 2006). Previously, it was suggested that the system response changed post-1993 and Turner et al. (2012) found a positive time trend in a model of hypoxia response to nitrogen. The stock of phosphorus is highly correlated with time ($\rho = 0.71$, $p < 0.01$). Thus, observable variables (nutrients) which can impact hypoxia are included, instead of the time trend which proxies for accumulation of phosphorus and may include other unobservable factors.

We further find evidence for the effect of unusual current conditions and hurricanes (via their interactions with phosphorus stocks). The presence of unusual currents has a negative impact on the size of the hypoxic zone ($p < 0.01$). Hurricanes are a major disturbance and may affect current and future hypoxia formation in complicated ways. While hurricanes, by mixing the water column, may reduce the size of hypoxia, hurricanes may also be increasing oxygen

by USGS, which use two alternative models, one empirical (http://www.gulfhypoxia.net/news/default.asp?XMLFilename=201306191312.xml), and another one based on the Streeter-Phelps process with calibrated parameters (http://snre.umich.edu/scavia/wp-content/uploads/2013/06/2013-Gulf-of-Mexico-Hypoxic-Forecast_UM.pdf). The LUMINATE model was most precise for 2011 and 2012 and was second-best in 2013. While an improved process-level understanding of hypoxia formation remains needed, the empirical relationship used in LUMINATE appears to be on par or better than the existing models used for hypoxia policy evaluation.
demand from the sediments, so the net impact of a hurricane is an empirical question. Across hypoxia observations from 1985 to 2013, the average size of the hypoxic zone is 12,825 km² for non-hurricane years and 16,630 km² for years in which hurricanes were observed (a univariate t-test, assuming unequal variances, yields a p-value of 0.052). In the model, the null hypothesis of no impact of hurricanes is rejected with p<0.001. We find that the impact of hurricanes appears to be interacting with nutrients, especially phosphorus.

**Cover crops scenario and estimated impact on Gulf hypoxia**

The empirical model of Gulf hypoxia is estimated using USGS May nitrogen and phosphorus load estimates for the amount of nutrients reaching the Gulf of Mexico, while the cover crops scenario presented in this paper simulates load reductions at the outlets of the Upper Mississippi and at the Ohio-Tennessee River basins. Therefore, a link between the scenario and its impact on nutrient loads to the Gulf needs to be created. We follow a simple procedure and use (a) USGS-reported estimates for nutrient loadings originating from the Upper Mississippi River basin and the Ohio-Tennessee River basin and (b) estimated delivery ratio in the main stem of the Mississippi River for nitrogen and phosphorus from White et al. (2014). Using this information, along with SWAT-simulated impact of cover crops on May N and P, we compute the relative reduction in the nutrient loads to the Gulf and use the adjusted nutrient values as inputs into the empirical model of the hypoxic zone. Keeping loads from other contributing basins (Missouri, Arkansas-White-Red, and Lower Mississippi) constant, we assume that each nutrient’s monthly load unit reduction contributes \(d_j(1 - r_{ijt})\) units of reduction to the Gulf.

---

7 A nonparametric Mann-Whitney test (one-sided) yields a p-value of 0.07.
8 USGS estimates of nutrient flux at the outlet of UMRB (http://toxics.usgs.gov/hypoxia/mississippi/flux_est/MISS-THEB.html) and OHTRB (http://toxics.usgs.gov/hypoxia/mississippi/flux_est/OH-GRAN.html) were used.
where \( j = N, P, i = UMRB, OTRB, \) and \( t = 1981, ..., 2010, \) and where \( r_{ijt} \) represent the SWAT model-simulated reductions in monthly nutrient loads. Weighing the USGS estimates of N and P loads from the UMRB and OTRB by these factors, we adjust the USGS estimates of N and P reaching the Gulf, and employ the final estimates in creating the counterfactual cover crops scenario. We assume a fixed delivery ratio of 0.87 for N and 0.9 for P, using estimates from White et al. (2014). The following table presents estimates of May N and P load reductions as simulated by SWAT.

Note that in comparison to mean annual N and P reductions (Table 5), simulated May mean N reduction is comparable to the annual values for the UMRB while quite smaller for the OTRB. Impacts on P are simulated to be a relatively small reduction for the UMRB and a small net gain in monthly P values for OTRB (although the annual P reductions are significant in both basins). In the cover crops scenario, May nitrogen loads reaching the Gulf are reduced by 14.7%, on average (s.d.=24%), while May phosphorus loads are reduced by 8.6%, on average (s.d.=6%), over the period from 1981 to 2010.

Estimated expected hypoxia reductions are significant (mean annual reduction in the size of the zone is estimated to be 47%), although the effectiveness of the scenario varies significantly over the simulation period, as would be expected given variable reductions in spring nutrients simulated by SWAT. The national hypoxia Action Plan sets the target in terms of a five-year running average of the hypoxic zone, which suggests that a smoothed relationship may be of interest to policymakers. Figure 6 presents the baseline scenario and the simulated impact of widespread application of cover crops on the five-year average of the Gulf hypoxic zone. The Action Plan target of 5,000 km\(^2\) is depicted by a dashed line. These results suggest that the cover crops scenario is likely not sufficient to reach the goal. The mean five-year hypoxia is estimated
to be 7,175 km² (s.d.=3,590 km²), and the hypoxia goal is reached in less than one-third of the five-year periods between 1990 and 2010.

The results simulated by SWAT suggest that cover crops are generally effective in reducing N and P, especially in terms of reducing total annual nutrient loads. Spring nutrient load percent reductions due to cover crops are simulated to be significantly smaller than annual reductions, which is reasonable given that cover crops are most effective at mitigating nutrient loss when traditional crops are not demanding nutrients. The reduction of pollutants at the local watershed level and specifically in densely cropped areas is much higher than the reduction at the outlet of the UMRB/OHTB which drains to the Gulf. This fact highlights the important benefits of pollution mitigation in intensively managed areas where local environmental problems exist and need remediation.

The establishment of rye as a winter cover crop is effective in reducing soil erosion, and both sediment-bound and soluble forms of nutrients, and the results here are generally in agreement with estimated impacts reported by IDALS (2013). Combining cover crops with other conservation practices would be expected to be even more effective in reducing soil and nutrient pollutant losses. The findings on the impact of cover crops on Gulf hypoxia are consistent with the existing literature.

The 2001 Action Plan estimated that a 30% reduction in the nitrogen load would likely be needed to achieve the hypoxia target. Subsequent research called for nitrogen load reductions closer to 35 to 45% (Scavia et al. 2003; Justić et al. 2003). Rabotyagov et al. (2014), using a similar empirical relationship, found that simultaneous 30% reduction in spring N and P would have been sufficient to reduce the size of the hypoxic zone to less than 5000 km². The preliminary evidence suggests that even a widespread adoption of cover crops, while likely
having a fairly large impact in terms of hypoxia reductions, appears not sufficient in terms of reaching the national Gulf hypoxia goal.

**Summary and Final Remarks**

In this paper, we discuss the importance of developing integrated assessment models to support the design and implementation of policies to address water quality problems associated with agricultural pollution. We describe a new modeling system, LUMINATE, which links land use decisions made at the field scale in the Upper Mississippi, Ohio, and Tennessee basins with local water quality effects and hypoxia in the Gulf of Mexico. We illustrate the model’s capabilities with a simple scenario where cover crops are implemented over a large expanse of the watershed.

In future work, we plan to integrate the LUMINATE modeling system with evolutionary algorithms to find spatially optimized locations for the placement of cover crops and other conservation practices to achieve a wide range of environmental improvements. Scenarios that interface optimal placement of conservation practices with possible future climate scenarios will also be explored.
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Figure 1. Location of the Upper Mississippi River Basin (URMB) and the Ohio-Tennessee River Basin (OTRB) within the Mississippi-Atchafalaya River Basin (MARB).
Figure 2. Modeling Schematic for LUMINATE

Input data: land use, soil, climate, topographic management

Land use, management, climate change, and/or other scenarios

SWAT UMRB and OTRB models

Nutrient loads

Gulf of Mexico hypoxic zone model

Contraction or expansion of hypoxic zone

Economic land use model

Optimization: evolutionary algorithm (EA)
Figure 3. Locations of the UMRB and OTRB within the US, the main tributaries, and monitoring site locations within each study region.
Figure 4. Graphical representation of the empirical relationship between areal extent of hypoxia (z-axis, km²), and N and P (x and y axes, metric tons). Relationship depicted for hypothetical May 2004 loadings (lagged loadings held at historical levels).
Figure 5. Observed and model-predicted areal extent of Gulf of Mexico hypoxia, and 95% confidence intervals for model prediction (2011-2013 observations were used to create out-of-sample predictions). The lower 95% confidence interval bounds were estimated to be negative for 1985-6 and 1988-9 (lower bound for 1987 is 280.3 km², which is too small to be shown on the graph).
Figure 6. The annual baseline and counterfactual hypoxia scenarios, 5-year mean hypoxia, 1990-2010 (structural component of the estimated relationship is used).
Table 1. Key data layers incorporated in the UMRB and OTRB SWAT models

<table>
<thead>
<tr>
<th>Data layer</th>
<th>Description of data layer</th>
<th>Primary data sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily climate</td>
<td>Daily precipitation and maximum and minimum temperature; other data generated in model</td>
<td>NCDC-NOAA (2012)</td>
</tr>
<tr>
<td>Soil map / layer data</td>
<td>1:250,000 soil map; pertinent soil layer attributes included for each soil type</td>
<td>USDA-NRCS (1994; 2012b)</td>
</tr>
<tr>
<td>Major dams / reservoirs</td>
<td>Key reservoirs on main channels of the Ohio and Mississippi Rivers, and major tributaries</td>
<td>USACE (2012)</td>
</tr>
<tr>
<td>Topographic</td>
<td>30 m digital elevation model (DEM) data used to characterize slopes and slope lengths</td>
<td>USGS (2006)</td>
</tr>
<tr>
<td>Land Use</td>
<td>Assignment of crop rotations or other landuse to each subwatershed; dominant rotations were 2-year sequences of corn and soybean</td>
<td>USDA-NASS (2012)</td>
</tr>
<tr>
<td>Point Sources</td>
<td>N and P discharged from thousands of waste treatment plants and other point sources across the two study regions</td>
<td>Maupin and Ivahnenko (2011); Robertson (2013)</td>
</tr>
<tr>
<td>Subsurface tile drainage</td>
<td>Installed at assumed depth of 1.2 m in poorly drained and relatively flat soils (&lt; 2% slope)</td>
<td>Sugg (2007); Neitsch et al. (2009)</td>
</tr>
<tr>
<td>Tillage practices</td>
<td>Notill, mulch till, reduced till, and conventional till practices represented as a function of tillage passes and residue cover, and other parameters</td>
<td>Baker (2011); Neitsch et al. (2009)</td>
</tr>
<tr>
<td>Fertilizer and manure</td>
<td>Nitrogen and phosphorus rates applied in inorganic fertilizer and manure; average rates used for landscapes located within each state</td>
<td>IPNI (2010)</td>
</tr>
<tr>
<td>Other conservation practices</td>
<td>Proxy approach used to represent terraces, contouring, and other practices as a function of slope and slope length</td>
<td>USDA-NRCS (2012a); Arabi et al. (2008); Neitsch et al. (2009)</td>
</tr>
</tbody>
</table>
Table 2: Mean annual (1981-2010) SWAT results at the outlets of UMRB and OTRB under the baseline and a cover crop scenario

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>UMRB</th>
<th>OTRB</th>
<th>Reduction (%)</th>
<th>Reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total crop area (ha)</td>
<td>23000000</td>
<td>10130000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop area &lt;5% (ha)</td>
<td>21900000</td>
<td>10050000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow (m³/s)</td>
<td>4,095</td>
<td>4,064</td>
<td>31</td>
<td>7,716</td>
</tr>
<tr>
<td>Sediments (t)</td>
<td>29,008,718</td>
<td>21,344,125</td>
<td>766,4593</td>
<td>43,661,137</td>
</tr>
<tr>
<td>NO₃-N (t)</td>
<td>405,120</td>
<td>332,558</td>
<td>72,562</td>
<td>313,191</td>
</tr>
<tr>
<td>TN (t)</td>
<td>536,361</td>
<td>425,508</td>
<td>110,853</td>
<td>434,581</td>
</tr>
<tr>
<td>TP (t)</td>
<td>40,349</td>
<td>31,877</td>
<td>8,472</td>
<td>48,605</td>
</tr>
</tbody>
</table>

Legend:
- Baseline
- Cover Crop
- Reduction
- Reduction (%)
<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Baseline</th>
<th>Cover crop</th>
<th>Reduction in t</th>
<th>% Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sediments (t)</td>
<td>7,2669,856</td>
<td>59,609,299</td>
<td>13,060,557</td>
<td>18.0</td>
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<tr>
<td>NO₃-N (t)</td>
<td>718,311</td>
<td>588,764</td>
<td>129,547</td>
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<td>TN (t)</td>
<td>970,942</td>
<td>779,939</td>
<td>191,004</td>
<td>19.7</td>
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<tr>
<td>TP (t)</td>
<td>88,954</td>
<td>73,280</td>
<td>15,674</td>
<td>17.6</td>
</tr>
<tr>
<td>% area treated</td>
<td>Reductions (kg/ha)</td>
<td>Cost ($/reduced kg)</td>
<td>Cost ($/reduced kg)</td>
<td></td>
</tr>
<tr>
<td>----------------</td>
<td>-------------------</td>
<td>---------------------</td>
<td>---------------------</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UMRB</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nitrogen</td>
<td>95</td>
<td>8.38</td>
<td>7.39</td>
<td>10.34</td>
</tr>
<tr>
<td>Phosphorus</td>
<td></td>
<td>0.39</td>
<td>159.96</td>
<td>223.95</td>
</tr>
<tr>
<td>Total Costs ($mil)</td>
<td></td>
<td>1,355.2</td>
<td>1,897.3</td>
<td></td>
</tr>
<tr>
<td>OTRB</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Nitrogen</td>
<td>99</td>
<td>13.65</td>
<td>4.53</td>
<td>6.35</td>
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<tr>
<td>Phosphorus</td>
<td></td>
<td>0.72</td>
<td>86.35</td>
<td>120.89</td>
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<tr>
<td>Total costs ($mil)</td>
<td></td>
<td>621.90</td>
<td>870.70</td>
<td></td>
</tr>
<tr>
<td>Cost cover crops</td>
<td></td>
<td>61.8$/ha ($25/ac)</td>
<td>86.6 $/ha ($35/ac)</td>
<td></td>
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</tbody>
</table>
Table 5. Hypoxia model parameter estimates and fit statistics

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t Value</th>
<th>p-value</th>
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</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-670443</td>
<td>170396</td>
<td>-3.93</td>
<td>0.0017</td>
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<tr>
<td>Hurricane</td>
<td>164110</td>
<td>183151</td>
<td>0.90</td>
<td>0.3865</td>
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<td>Currents</td>
<td>-13637</td>
<td>2776</td>
<td>-4.91</td>
<td>0.0003</td>
</tr>
<tr>
<td>Log10(current year t May N)</td>
<td>33892</td>
<td>9630</td>
<td>3.52</td>
<td>0.0038</td>
</tr>
<tr>
<td>Log10(year t-1 May N)</td>
<td>29368</td>
<td>8381</td>
<td>3.50</td>
<td>0.0039</td>
</tr>
<tr>
<td>Log10(year t-2 May N)</td>
<td>24844</td>
<td>7146</td>
<td>3.48</td>
<td>0.0041</td>
</tr>
<tr>
<td>Log10(year t-3 May N)</td>
<td>20321</td>
<td>5936</td>
<td>3.42</td>
<td>0.0045</td>
</tr>
<tr>
<td>Log10(year t-4 May N)</td>
<td>15797</td>
<td>4767</td>
<td>3.31</td>
<td>0.0056</td>
</tr>
<tr>
<td>Log10(year t-5 May N)</td>
<td>11273</td>
<td>3681</td>
<td>3.06</td>
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<tr>
<td>log10P, year t TP</td>
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<td>4961</td>
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<td>Nstock5</td>
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<tr>
<td>Pstock5</td>
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<td>0.0854</td>
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<td>hurrStockN5</td>
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<tr>
<td>AR1 (θ₁)</td>
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<td>0.1628</td>
<td>2.48</td>
<td>0.0274</td>
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<tr>
<td>AR2 (θ₂)</td>
<td>0.8117</td>
<td>0.1511</td>
<td>5.37</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Model Fit

| Regression R-Square       | 0.9503     | Observations | 25 |
| Total R-Square            | 0.9085     | d.f. error   | 13 |
| SBC                       | 485.372678 | AIC           | 470.746168 |
| Log Likelihood            | -223.37308 |              |     |
| Durbin-Watson             | 2.5251     |              |     |

<table>
<thead>
<tr>
<th>Year</th>
<th>UMRB</th>
<th>OHTRB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent Reduction in May N</td>
<td>Percent Reduction in May P</td>
</tr>
<tr>
<td>1981</td>
<td>38.8</td>
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<tr>
<td>1982</td>
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<td>1983</td>
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<tr>
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<td>1985</td>
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<td>43.3</td>
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