

## **Cross-Watershed Leakage of Agricultural Nutrient Runoff**

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### Abstract

Agricultural nutrient runoff has been a major contributor to hypoxia in many downstream coastal ecosystems. Although programs have been designed to reduce nutrient loading in individual coastal waters, cross watershed interdependencies of nutrient runoff have not been quantified due to a lack of suitable modeling tools. Cross-watershed pollution leakage can occur when nutrient runoff moves from more to less regulated regions. We illustrate the use of an Integrated Assessment Model (IAM) that combines economic and process-based biophysical tools to quantify Nitrogen loading leakage across three major US watersheds. We also assess losses in consumer and producer surplus from decreased commodity supply and higher prices when nutrient delivery to select coastal ecosystems is restricted. Reducing agricultural N loading in the Gulf of Mexico by 45% a) increases loading in the Chesapeake Bay and Western Lake Erie by 4.2% and 5.5%, respectively, and b) results in annual surplus losses of \$7.1 and \$6.95 billion with and without restrictions on leakage to the Chesapeake Bay and Lake Erie, respectively.

**Keywords:** Pollution Leakage, Watershed, Nitrogen, Hypoxia, Agriculture, Hydro-economic model, Prices.

Agricultural nutrient runoff in individual watersheds has been extensively studied (Bosch et al., 2018; Kling et al., 2014; Liu et al., 2020; Rabotyagov et al., 2014; Rabotyagov et al., 2010; Ribaudo et al., 2001; Secchi et al., 2011). However, due to modeling limitations, no structural estimates of cross-watersheds nutrient loading interdependencies have been produced. Cross-watershed leakage can occur when nutrient intensive production moves from more to less regulated regions (Shortle et al., 2021). Previous studies document potential increase in the acreage of fertilizer intensive crops outside of Mississippi Atchafalaya River Basin (MARB) in the US when loading in the Gulf of Mexico is reduced (Ribaudo et al., 2001; Marshall et al., 2018; Xu et al., 2022). However, none of the prior studies provide estimates for the magnitude of leakage or assess the costs of loading reduction programs controlling for cross-watershed leakage. We address this gap in the literature by presenting an Integrated Assessment Model (IAM) designed to quantify nutrient leakage across three major hypoxic coastal ecosystems in the US.

Agriculture is a major nonpoint source of nutrient pollution in rivers, lakes, estuaries, and coastal waters (Carpenter et al., 1998; Khanna et al., 2019; Shortle et al., 2021), resulting in eutrophication, harmful algal bloom, and hypoxia (Chang et al., 2021; Camargo & Alonso, 2006; Zillén et al., 2008). Hypoxia disrupts nutrient cycling, increases the acidity of the water column, damages marine habitats, degrades biodiversity, decreases fish catch, and limits recreation opportunities (Chang et al., 2021; Diaz & Rosenberg, 2008; Du et al., 2018). Hypoxic zones are sometimes called “dead zones” because fish either die due to a lack of dissolved oxygen or relocate to other, more habitable areas. Although hypoxia can occur naturally, human activities, including agricultural production,

increase the size and the number of dead zones. More than 400 coastal marine systems worldwide have hypoxic zones (Diaz & Rosenberg, 2008; Du et al., 2018).

Northern Gulf of Mexico, Chesapeake Bay, and Western Lake Erie suffer from some of the largest and most publicized hypoxic zones in the US. Large quantities of nutrient in these ecosystems come from agricultural production in the Mississippi Atchafalaya River Basin (MARB) (Gupta et al., 2021; Rabotyagov et al., 2014; Diaz & Rosenberg, 2008), Chesapeake Bay Watershed (CBW) (Chang et al., 2021), and Maumee River Watershed (MRW) (Liu et al., 2020), respectively (*Figure 1*). Additional background for these watersheds is provided in appendix 1.1.

Programs have been established in these watersheds to reduce nutrient loading. The Mississippi River/Gulf of Mexico Hypoxia Task Force aims to reduce the size of the Hypoxic zone in the Gulf to 5,000 km<sup>2</sup> by 2035, which requires reducing nitrogen (N) loading by 45% (USEPA, 2014, Rabotyagov et al., 2014, Shortle et al., 2021). The Chesapeake Bay Total Maximum Daily Load (TMDL) seeks to reduce N loads by 25% relative to 2009 values (Chang et al., 2021). The objective of the revised 2012 Great Lakes Water Quality Agreement (GLWQA) is to reduce total Phosphorus (P) loading by 40% relative to 2008 (Liu et al., 2020). Although the objectives of these programs individually have been extensively studied, the interdependencies in terms of cross-watershed nutrient loading leakage have yet to be quantified.

Cross-watershed nutrient leakage can be as a consequence of regional loading reduction efforts because a decrease in fertilizer use or adoption of some of the best management practices (Rabotyagov et al., 2014) can decrease output and increase prices if the targeted region produces a large share of market supply. Higher prices incentivize producers in less regulated regions to increase

production. Thus, nutrient loading can “leak” from more to less regulated watersheds (Shortle et al., 2021).

Our main research objective is to quantify cross-watershed leakage of the coastal N loading from agricultural production in MARB, CBW, and MRW. We assess leakages in response to reducing agricultural N loading from MARB to the Gulf of Mexico by 45% and from the CBW to the Chesapeake Bay by 25%. These objectives are examined individually and in combination with explicit account of N loading leakage from more to less regulated watersheds. We also assess the consumer and producer losses from nitrogen loading reduction in MARB and CBW with alternate N leakage constraints. Although P is the primary nutrient of concern in the MRW, understanding potential impacts on N loading is important to mitigate algal blooms in western Lake Erie.

## Methods

We evaluate five scenarios that are benchmarked relative to the baseline business-as-usual solutions. In the first scenario (Gulf-45), the aggregate agricultural N delivery to the Gulf is reduced by 45% relative to the baseline, consistent with the EPA hypoxia task force goal. We quantify the impact on N loading the Chesapeake Bay and Western Lake Erie. In the second scenario (Gulf-45-R), delivery to the Gulf is reduced by 45% while the Chesapeake Bay and Lake Erie loadings are restricted to not exceed the outcomes observed in the baseline solution. In the third scenario (Bay-25), we impose a 25% reduction in agricultural N loading in the Chesapeake Bay relative to the baseline solutions, consistent with the Chesapeake Bay TMDL program, and quantify the impact on N loadings in the Gulf and Western Lake Erie. In the fourth scenario (Gulf-45\_Bay-25-R), we combine the 45% N loading reduction in the Gulf and a 25% N loading reduction in the Chesapeake Bay with a constraint that prevents relocation of delivery to Lake Erie relative to the baseline. The last scenario

(Gulf-45\_Bay-25-NL) extends the previous one by constraining the acreage in the rest of the country (ROC), outside of MARB, MRW, and CBW to the acreage observed in the baseline solutions.

In each scenario, we estimate the opportunity cost of reducing N loading with and without constraints restricting cross-watershed N leakage. The opportunity cost includes consumer and producer losses from decreases in the supply and increases in prices of affected major commodities. In addition, we report changes in county scale N use in each scenario to illustrate potential implications for regional water quality.

We use an Integrated Assessment Model (IAM) for linking biophysical and human systems in agricultural production and multi-watershed N runoff and loading in the coastal waters. The Integrated Hydro-Economic Agricultural Land use (IHEAL) model, combines a price endogenous partial equilibrium commodity market representation, county scale agricultural land use, and process-based Soil and Water Assessment Tool (SWAT) (Xu et al., 2022). The model is extended to include CBW and MRW with associated specifications for county scale agricultural production and downstream coastal nutrient loading. Unlike previous studies, we explicitly account for price feedbacks and multi-watershed nutrient runoff and leakage (Rabotyagov et al., 2010, 2014; McLellan et al., 2015; Easton et al., 2020; Xu et al., 2022).

## Results

We find that reducing agricultural N loading in the Gulf of Mexico by 45% can increase N loadings in the Western Lake Erie and the Chesapeake Bay by 4% and 6% respectively. We also observe that the cost of reducing agricultural N loading in the Chesapeake Bay by 25% is much lower (\$40 million) than the cost of reducing loading in the Gulf of Mexico by 45% (\$6.95 billion) because a) the latter has a greater reduction target than the former, and b) MARB is substantially larger than

CBW and produces a much larger share of US agricultural commodities. Preventing cross-watershed leakage in response to reducing N loading in the Gulf by 45% increases market cost by \$150 million.

We present the Gulf, Chesapeake Bay, and Western Lake Erie impacts when loading in the Gulf and/or the Chesapeake Bay is individually or jointly curbed. The results are presented in Tables 1-4. Tables 1 and 2 show price, opportunity cost, and N loading results across scenarios, while Tables 3 and 4 report corresponding land use and production results, respectively. Each table shows results for the contiguous US, individual watersheds, and the rest of the country (ROC), where applicable. Each table has five scenario results.

### ***Gulf-45***

The results in Table 1 show that corn, soybean, and wheat prices increase by 26.67%, 23.47%, and 5.43%, respectively, while sorghum price decreases by 22.56% as US production of more N intensive corn, wheat and soybean as a rotation crop decreases and production of less N-intensive sorghum increases (*Table 4*). In MARB, all crop acreages decline except wheat (table 3). However, in the ROC, all crop acreages increase except wheat. In addition, corn acreages increase while soybean acreages decrease in CBW and MRW. Lower MARB corn production and a consequent price increase result in increased corn production in CBW, MRW, and ROC. Wheat acres move from CBW to MRW. Increased production of corn replaces soybean in MRW, wheat and soybean in CBW, and wheat in ROC (*Tables 3 and 4*, panels B, C, D, E). Although US acres for some crops increase, production of all crops except sorghum decreases (*Table 4*, Panel A) because production moves to less suitable lands relative to the baseline results.

As N-intensive crop production moves from MARB to other regions, so does N use and corresponding N loading. Table 2 shows that N use in MARB declines by 21.58% to reduce loading by 45%. N use increases by 5.78% in CBW and 10.19% in MRW. The corresponding N loadings in

the Chesapeake Bay and Western Lake Erie increase by 4.24% and 5.52%, respectively. These results are qualitatively similar to Ribaudo et al. (2001), where a 10% reduction in N use within the MARB increases onsite N loss in other regions by 1%.

### ***Gulf-45-R***

Changes in prices (*Table 1*) and US land use (*Table 3*) relative to the baseline are qualitatively similar to the previous scenario. The lower prices relative to the Gulf-45 scenario are due to greater aggregate production (*Table 4*). The additional Lake Erie and Chesapeake Bay N loading constraints effectively flatten the marginal production cost curves by rotating them clockwise relative to the Gulf-45 scenario, which results in greater output and lower prices, benefiting consumers but harming producers. As expected, combined consumer and producer surplus is lower than in the less constrained Gulf-45 (*Table 1*). Preventing cross-watershed leakage by restricting N loading in Lake Erie and the Chesapeake Bay to be at or below the baseline values increases the annual opportunity cost of Gulf loading reduction by \$0.15 billion relative to the Gulf-45 scenario.

Corn production slightly increases in the Gulf-45-R in MARB and decreases in CBW, MRW, and ROC relative to Gulf-45. Soybean production decreases in MARB and CBW and increases in MRW and ROC. Wheat production decreases in MARB, CBW, and MRW and increases in ROC. Sorghum moves from MARB to ROC. Corn acreage moves from MARB and MRW to CBW and ROC relative to the Gulf-45 scenario (*Table 3*). Soybean acres move from MARB and CBW to MRW and ROC, while wheat acres move to ROC from MARB, MRW, and CBW (*Table 3*). Corn production in MARB increases even though acreage decreases as N use declines (*Table 4*) because production

moves to more productive MARB lands relative to the Gulf-45 scenario, where relocation to other watersheds was an option.

### ***Bay-25***

As expected, this loading reduction objective has a much smaller impact on prices and leakage than the 45% reduction in the Gulf loading (*Table 1*). Still, prices of N-intensive crops slightly increase while sorghum prices decrease relative to baseline. In percentage terms, corn, soybean and wheat acres and production decrease significantly in CBW (*Tables 3 and 4*). As expected, in CBW, corn, as the most N-intensive crop, experiences the largest decrease in acreage (14.57%) and production (16.72%).

While N use and runoff decrease in CBW as intended, slight increases are observed in MARB and MRW. N deliveries to the Gulf and Lake Erie increase by 360 (0.08%) and 3.5 thousand metric tons (1.36%), respectively (*Table 2*). The opportunity cost of the TMDL program in the Chesapeake Bay is \$0.04 billion and, as expected, is much smaller than in the Gulf N loading reduction scenarios (*Table 1*).

### ***Gulf-45\_Bay-25-R***

Similar to the results presented above, crop prices increase except for sorghum (*Table 1*). The magnitudes of price changes are comparable to the Gulf-45-R scenario because production in CBW represents a significantly smaller share of the commodity market than in MARB. Chesapeake Bay's 25% N loading reduction has a small effect on prices when imposed in isolation or in addition to the 45% reduction to the Gulf. Restricting leakage to Western Lake Erie produces negligible impact on prices when deliveries to the Gulf and to the Chesapeake Bay are curbed by 45% and 25%. A similar resemblance of results between Gulf-45\_Bay-25-R and Gulf-45-R is also observed for land use (*Table 3*), production (*Table 4*), and N loading (*Table 2*). The opportunity cost is \$7.19 billion, which is \$0.09

billion greater than Gulf-45-R (*Table 1*). Hence, the marginal opportunity cost of reducing N loading in the Chesapeake Bay, on top of the 45% Gulf reduction with restriction on loading in Lake Erie, is more than twice as expensive as reducing the Chesapeake Bay loading independently.

### ***Gulf-45\_Bay-25-NL***

The purpose of this scenario is to examine the impact of limiting the relocation of the N-intensive crop production from the regulated MARB and CBW to other areas, including ROC. As expected, this scenario produces a significantly greater impact on crop prices as the opportunity to offset the decreased production in MARB and CBW by moving N-intensive crop production to other regions is limited. Prices of corn, soybean, wheat, and sorghum increase by 42%, 40%, 6%, and 14%, respectively, relative to baseline prices (*Table 1*). Unlike N loading reduction scenarios presented earlier, even sorghum prices increase when land use change in ROC is restricted. Crop prices increase even though aggregate wheat and sorghum acreages increase. Although loading leakage to Lake Erie is restricted and delivery to the Chesapeake Bay is curtailed by 25%, some corn acreage moves from the MARB to CBW and MRW (*Table 3*). Production of the four crops declines in all areas except for corn in MRW (*Table 4*). These changes in production result in an \$8.1 billion loss of consumer and producer surplus relative to the baseline scenario (*Table 1*). Hence, preventing relocation of N loading from MARB and CBW to other regions as deliveries to the Gulf and the Chesapeake Bay are reduced by 45% and 25%, respectively, costs an additional \$0.91 billion annually in consumer and producer benefits.

## **Discussion**

We observe in the Gulf-45 scenario that the annual consumer and producer loss from 45% N loading reduction to the Gulf is \$6.95 billion (*Table 1*). This estimate is greater than the \$2.7 billion in

Rabotyagov et al. (2014) because of differences in the modeling framework and scope. Our estimates represent consumer and producer surplus losses, taking into account price changes. On the other hand, Rabotyagov et al. (2014) estimate the operational costs of implementing best management practices for reducing N runoff and treat prices as fixed. Our approach is similar to Xu et al. (2022), who provide a comparable cost estimate of \$6 billion. The difference is that in Xu et al. (2022), MRW and CBW production activities are not modeled explicitly in terms of per acre N use, resulting in a loss of accuracy. They also do not account for N deliveries to other areas besides the Gulf of Mexico.

In the Gulf-45-R scenario, N deliveries to Lake Erie and Chesapeake Bay are restricted, which limits the opportunity to offset decreased corn production in MARB by relocating to other watersheds when loading in the Gulf is constrained. The relocation of corn to more productive lands within MARB results in the displacement of other crops. N use in MRW and CBW is lower than in the Gulf-45 scenario but greater than in the baseline (Table 2). Even though N deliveries to Lake Erie and the Chesapeake Bay are the same as in the baseline as required by the N delivery constraint, local water quality may decline as N use increases in some counties.

In the Bay-25 scenario, some corn production moves from CBW to MARB, MRW, and ROC. Soybean and wheat production decreases in MARB and increases in ROC. Although sorghum is not produced in CBW, the TMDL program results in a relocation of sorghum production from MARB to ROC as MARB's corn production expands in response to decreased production in CBW. The annual consumer and producer loss due to a 25% N loading reduction to the Chesapeake Bay is \$0.04 billion. This estimate is significantly smaller than Kaufman et al. (2014) operational best management practice implementation costs for N, P, and sediment reduction in Chesapeake Bay..

The opportunity cost of nutrient loading reduction increases with limiting the relocation to other watersheds in the Gulf-45\_Bay-25-R and Gulf-45\_Bay-25-NL scenarios. Previous studies have

called for further research to determine the increase in the acreage of fertilizer-intensive crops outside of MARB in the US when loading in the Gulf of Mexico is reduced (Ribaudo et al., 2001; Marshall et al., 2018; Xu et al., 2022). This study estimates the magnitude of N leakage and costs associated with controlling cross-watershed leakage, suggesting a need for policies that consider both local and regional impacts to mitigate nutrient pollution in water bodies effectively.

In addition to N deliveries to downstream coastal ecosystems, fertilizer use can impact local water quality. The IHEAL model provides county-scale crop production and N use in response to reducing nutrient loadings in downstream ecosystems. Figure 2 shows changes in county scale N use relative to the baseline use for each scenario. In the scenarios where loading in the Gulf is restricted, the most significant reduction in N use takes place in the Upper Mississippi River Basin (UMRB), a major source of nutrient loading in the Gulf that has been identified for targeted best management practices in prior literature (Rabotyagov et al., 2010; Rabotyagov et al., 2014; White et al., 2014; Marshall et al., 2018; Xu et al., 2022). Some counties in the MARB with smaller delivery ratios increase N use even in the scenarios with a 45% reduction in delivery to the Gulf. Hence, leakage of N use and runoff is important to account for not only across the major watersheds like MARB, CBW, and MRW but also within those regions. The local water quality impacts of reducing N deliveries to outlets like the Gulf of Mexico should be considered as part of policy evaluation.

The findings of our study shed light on the interdependence of reducing nutrient loading to downstream coastal waters, corresponding upstream land use changes, and associated consumer and producer costs. However, the implications of these changes extend beyond mere acreage adjustments and involve intricate trade-offs between crop types, soil suitability, and environmental considerations. Exploring the long-term sustainability of changes in land use and their potential implications for soil health, biodiversity, and ecosystem services warrants attention in future research endeavors. Also,

nutrient-loading reduction strategies entail inherent trade-offs between environmental conservation goals, agricultural productivity, and economic welfare. While we quantify some of the costs, a more comprehensive assessment of trade-offs and co-benefits, such as improved water quality, biodiversity conservation, and climate resilience, can be helpful for informed decision-making. Integrating multidimensional criteria and adopting holistic evaluation frameworks could facilitate a more comprehensive and sustainable approach to nutrient management.

While the study provides original estimates of N leakage across major watersheds and provides a methodology that can be applied in similar settings, the assumptions and associated limitations imply plenty of room for further work. For example, estimation of N loading in the downstream waters relies on fixed delivery ratios obtained from prior literature. Constancy of delivery ratios is a reasonable assumption in the absence of better estimates. However, the analysis may benefit from updated delivery ratios that may change depending on upstream land use. The analysis also includes agricultural N delivery from only four major commodities. Future work should include N deliveries from production of an extended set of crops and livestock industry. Also, explicit inclusion of best management practices for managing nutrient runoff may improve the accuracy of results.

## Conclusion

We estimate cross-watershed N leakage when agricultural deliveries to the Gulf and the Chesapeake Bay are reduced by 45% and 25% individually and jointly according to the objectives of the Gulf Hypoxia Task Force and Chesapeake Bay TMDL (Marshall et al., 2018; Shortle et al., 2021). We evaluate five N loading management scenarios, including a) a 45% Gulf agricultural N loading reduction, b) a 45% Gulf loading reduction and no leakage to Western Lake Erie and the Chesapeake Bay, c) a 25% Chesapeake Bay loading reduction, d) a 45% and 25% loading reductions in Gulf and to the Chesapeake Bay, respectively, with a constrained loading in Western Lake Erie, and e) a 45%

and 25% reductions in the Gulf and the Chesapeake Bay loadings, respectively, with no leakage to rest of the country. For scenarios a) and c), we provide estimates of cross-watershed leakage, and for each scenario, we estimate the opportunity cost in terms of foregone consumer and producer surplus relative to the baseline.

We contribute to previous literature with a new IAM for evaluating cross-watershed leakage interdependencies. The model estimates N loading using a price endogenous partial equilibrium commodity market formulation, spatial SWAT parameters for crop production and N leaching, and county scale delivery ratios for each of the three watersheds. The partial equilibrium model links county scale production activities via market supply and demand, which allows for leakage across watersheds. This approach differs from the previous studies that model best management practices but do not explicitly account for price feedback and pollution leakage, do not account for price impacts and consumer and producer welfare losses, and do not provide leakage estimates.

Reducing N loading in the Gulf by 45% can result in relocation of N-intensive agricultural production, mainly corn, from MARB to CBW and MRW. Unless the Gulf loading reduction is accompanied with corresponding efforts for Western Lake Erie and the Chesapeake Bay, the N deliveries to these water bodies can increase by 4.24% and 5.52%, respectively. This susceptibility emphasizes the significance of Chesapeake Bay TMDL and the importance of explicitly including N into the Maumee Watershed Nutrient TMDL even though P is the primary nutrient of concern. Since reductions in N loading to the Gulf can increase nutrient pressure in the Western Lake Erie and Chesapeake Bay, it is important that effective programs are in place to prevent or mitigate the effect in the receiving waters. The consumer and producer benefit loss is marginally greater for the coordinated multi-watershed strategy relative to the Gulf only program. The cost of reducing

agricultural N loading in the Gulf of Mexico increases from \$6.95 to \$7.1 billion if leakages to the Chesapeake Bay and Western Lake Erie are avoided.

Reducing N loading in the Chesapeake Bay by 25% in isolation results in a small increase of N deliveries to the Gulf (0.08%) and Lake Erie (1.36%), with an opportunity cost of \$0.04 billion. As expected, the consumer and producer surplus loss from the Chesapeake Bay N loading TMDL is much smaller than the corresponding cost of the Gulf of Mexico Hypoxia Task Force goal because agricultural production in MARB is vastly greater than in the CBW. Hence, regulations in MARB have more significant impacts on prices and economic benefits for consumers and producers. The consumer and producer cost of reducing N deliveries to the Gulf of Mexico and the Chesapeake Bay by 45% and 25%, respectively, with no leakage to the Western Lake Erie, is \$7.19 billion. Hence, the cost of reducing delivery to the Chesapeake Bay by 25% in addition to the reduction of delivery to the Gulf by 45% costs an additional \$0.09 billion relative to the N delivery reduction to the Gulf with no leakage to the Chesapeake Bay and Western Lake Erie. The consumer and producer losses cost increases to \$8.1 billion in the most restricted scenario, where loading in the Gulf of Mexico and the Chesapeake Bay is reduced by 45% and 25%, respectively, and no N leakage to other areas of the US, including Western Lake Erie takes place.

## References

Bosch, D. J., Wagena, M. B., Ross, A. C., Collick, A. S., & Easton, Z. M. (2018). Meeting Water Quality Goals under Climate Change in Chesapeake Bay Watershed, USA. *Journal of the American Water Resources Association*, 54(6), 1239–1257. <https://doi.org/10.1111/1752-1688.12684>

Camargo, J. A., & Alonso, Á. (2006). Ecological and toxicological effects of inorganic nitrogen pollution in aquatic ecosystems: A global assessment. *Environment International*. 2006 Aug;32(6):831-49. <https://doi.org/10.1016/j.envint.2006.05.002>

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N., & Smith, V. H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications*, 8(3), 559–568.

Chang, S. Y., Zhang, Q., Byrnes, D. K., Basu, N. B., & van Meter, K. J. (2021). Chesapeake legacies: The importance of legacy nitrogen to improving Chesapeake Bay water quality. *Environmental Research Letters*, 16(8). <https://doi.org/10.1088/1748-9326/ac0d7b>

Diaz, R. J., & Rosenberg, R. (2008). Spreading dead zones and consequences for marine ecosystems. *Science*, 321(5891), 926–929.

Du, J., Shen, J., Park, K., Wang, Y. P., & Yu, X. (2018). Worsened physical condition due to climate change contributes to the increasing hypoxia in Chesapeake Bay. *Science of the Total Environment*, 630, 707–717. <https://doi.org/10.1016/j.scitotenv.2018.02.265>

Easton, Z.M., K. Stephenson, A. Collick, P.M. Fleming, E. Kellner, J. Martin, M. Ribaudo, and G. Shenk. 2020. Increasing effectiveness and reducing the cost of non-point source best management practice implementation: Is targeting the answer? Chesapeake Bay Science and Technical Advisory Committee Publication Number 20-002.

Gupta, G. V. M., Jyothibabu, R., Ramu, C. v., Yudhistir Reddy, A., Balachandran, K. K., Sudheesh, V., Kumar, S., Chari, N. V. H. K., Bepari, K. F., Marathe, P. H., Bikram Reddy, B., & Vijayan, A. K. (2021). The world's largest coastal deoxygenation zone is not anthropogenically driven. *Environmental Research Letters*, 16(5). <https://doi.org/10.1088/1748-9326/abe9eb>

Ishida, K., & Jaime, M. (2015). A Partial Equilibrium of the Sorghum Markets in US, Mexico, and Japan. *2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California* <https://doi.org/10.22004/AG.ECON.205708>

Kaufman, Z., Abler, D., Shortle, J., Harper, J., Hamlett, J., & Feather, P. (2014). Agricultural Costs of the Chesapeake Bay Total Maximum Daily Load. *Environmental Science & Technology*, 48(24), 14131–14138. <https://doi.org/10.1021/es502696t>

Khanna, M., Gramig, B. M., Delucia, E. H., Cai, X., & Kumar, P. (2019). Harnessing emerging technologies to reduce Gulf hypoxia. *Nature Sustainability*, 2, 889–891. <https://doi.org/10.1038/s41893-019-0381-4>

Kling, C. L., Panagopoulos, Y., Rabotyagov, S. S., Valcu, A. M., Gassman, P. W., Campbell, T., White, M. J., Arnold, J. G., Srinivasan, R., Jha, M. K., Richardson, J. J., Moskal, L. M., Turner, R. E., & Rabalais, N. N. (2014). LUMINATE: Linking agricultural land use, local water quality and Gulf of Mexico hypoxia. *European Review of Agricultural Economics*, 41(3), 431–459. <https://doi.org/10.1093/erae/jbu009>

Liu, H., Zhang, W., Irwin, E., Kast, J., Aloysius, N., Martin, J., & Kalcic, M. (2020). Best Management Practices and Nutrient Reduction: An Integrated Economic-Hydrologic Model of the Western Lake Erie Basin. *Land Economics*, 96(4), 510–530. <https://doi.org/10.3368/wple.96.4.510>

Marshall, E., Aillery, M., Ribaudo, M., Key, N., Sneeringer, S., Hansen, L., Malcolm, S. & Riddle, A. (2018). Reducing nutrient losses from cropland in the Mississippi/Atchafalaya River Basin: Cost efficiency and regional distribution, , ERR-258, U.S. Department of Agriculture, Economic Research Service.

McLellan, E., Robertson, D., Schilling, K., Tomer, M., Kostel, J., Smith, D., King, K., 2015. Reducing nitrogen export from the Corn Belt to the Gulf of Mexico: agricultural strategies for remediating hypoxia. *Journal of the American Water Resources Association*, 51(1), 263–289, <http://dx.doi.org/10.1111/jawr.12246>

Piggott, N. E., & Wohlgenant, M. K. (2002). Price elasticities, joint products, and international trade. *Australian Journal of Agricultural and Resource Economics*, 46(4), 487–500. <https://doi.org/10.1111/1467-8489.T01-1-00056>

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P. W., Arnold, J., Kurkalova, L., Secchi, S., Feng, H., & Kling, C. L. (2010). Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. *Ecological Applications*, 20(6), 1542–1555. <https://doi.org/10.1890/08-0680.1>

Rabotyagov, S. S., Campbell, T. D., White, M., Arnold, J. G., Atwood, J., Norfleet, M. L., Kling, C. L., Gassman, P. W., Valcu, A., Richardson, J., Turner, R. E., & Rabalais, N. N. (2014). Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone. *Proceedings of the National Academy of Sciences of the United States of America*, 111(52), 18530–18535. <https://doi.org/10.1073/pnas.1405837111>

Ribaudo, M. O., Heimlich, R., Claassen, R., & Peters, M. (2001). Least-cost management of nonpoint source pollution: Source reduction versus interception strategies for controlling nitrogen loss in the Mississippi Basin. *Ecological Economics*, 37(2), 183–197. [https://doi.org/10.1016/S0921-8009\(00\)00273-1](https://doi.org/10.1016/S0921-8009(00)00273-1)

Secchi, S., Gassman, P. W., Jha, M., Kurkalova, L., & Kling, C. L. (2011). Potential water quality changes due to corn expansion in the Upper Mississippi River Basin. *Ecological Applications*, 21(4), 1068–1084. <https://doi.org/10.1890/09-0619.1>

Shortle, J., Ollikainen, M, and Iho, A.,(2021) “Water Quality and Agriculture: Economics and Policy for Nonpoint Source Water Pollution” Palgrave Macmillan, Cham, Switzerland.

United States Department of Agriculture (USDA) Economic Research Service (ERS). (2019). Fertilizer Use and Price. <https://www.ers.usda.gov/data-products/fertilizeruse-and-price>. (Accessed 30 Oct 2019).

United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), (2020). US & All States County Data – Crops. Washington, DC. <http://www.nass.usda.gov/>. (Accessed 13 May 2021)

United States Environmental Protection Agency (USEPA), (2014). Mississippi River Gulf of Mexico Watershed Nutrient Task Force New Goal Framework (Accessed 30 December 2021) <https://www.epa.gov/sites/production/files/2015-07/documents/htf-goals-framework-2015.pdf>.

Westcott, P. C., & Hoffman, L. A. (1999). Price Determination for Corn and Wheat: The Role of Market Factors and Government Programs. (No.1488-2016-123383). Market and Trade Economics Division, Economic Research Service, US Department of Agriculture, Technical Bulletin No.1878 <https://doi.org/10.22004/AG.ECON.33581>

White, M. J., Santhi, C., Kannan, N., Arnold, J. G., Harmel, D., Norfleet, L., Allen, P., DiLuzio, M., Wang, X., Atwood, J., Haney, E., & Johnson, M. V. (2014). Nutrient delivery from the

Mississippi River to the Gulf of Mexico and effects of cropland conservation. *Journal of Soil and Water Conservation*, 69(1), 26–40. <https://doi.org/10.2489/jswc.69.1.26>

Xu, Y., Elbakidze, L., Yen, H., Arnold, J. G., Gassman, P. W., Hubbart, J., & Strager, M. P. (2022). Integrated assessment of nitrogen runoff to the Gulf of Mexico. *Resource and Energy Economics*, 67, 101279. <https://doi.org/10.1016/j.reseneeco.2021.101279>

Zillén, L., Conley, D. J., Andrén, T., Andrén, E., & Björck, S. (2008). Past occurrences of hypoxia in the Baltic Sea and the role of climate variability, environmental change and human impact. *Earth-Science Reviews*, 91(1–4), 77–92. <https://doi.org/10.1016/j.earscirev.2008.10.001>

## Figures and Tables

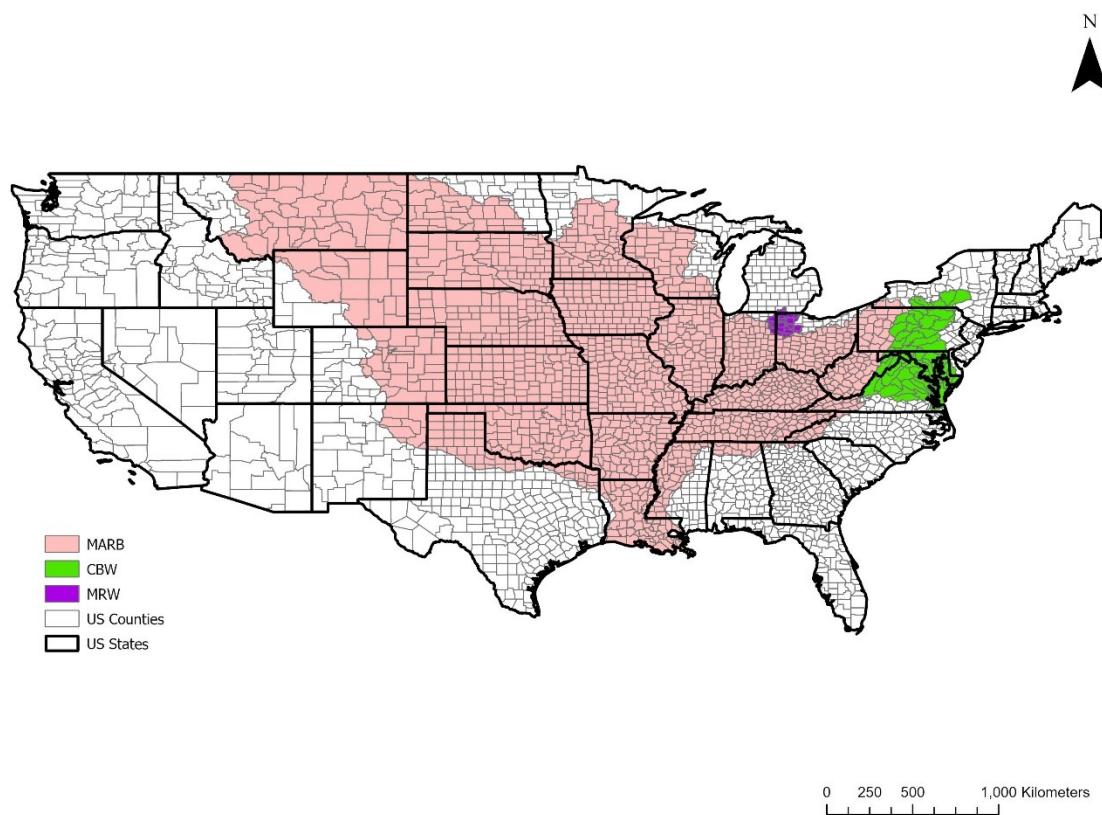
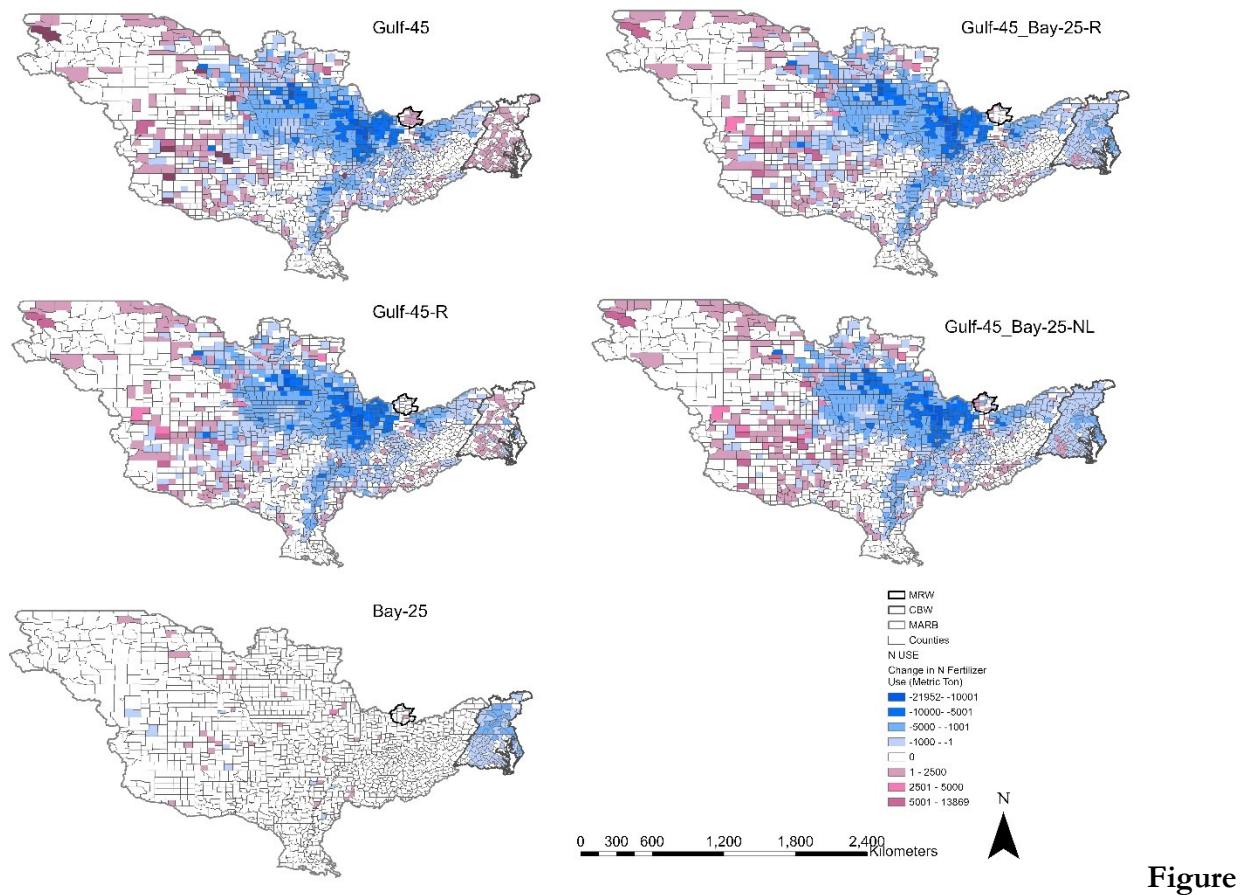


Figure 1. Mississippi Atchafalaya River Basin (MARB), Chesapeake Bay Watershed (CBW), and Maumee River Watershed (MRW).



**Figure**

## 2. N fertilizer use.

This figure presents county scale N fertilizer use changes by scenario relative to baseline. In Gulf-45 scenario, N fertilizer use increases in CBW and MRW in response to the 45% N loading reduction in MARB. In the Gulf 45-R, Gulf-45\_Bay-25-R and Gulf-45\_Bay-25-NL scenarios, some counties in CBW and MRW reduce N fertilizer use. In the Bay-25 scenario, N fertilizer use in CBW declines with minimal changes in MARB and MRW.

**Table 1. Results: Commodity prices and opportunity costs**

	<b>Baseline</b>	<b>Gulf-45</b>	<b>Gulf-45-R</b>	<b>Bay-25</b>	<b>Gulf-45_Bay-25-R</b>	<b>Gulf-45_Bay-25-NL</b>
<b>Prices (\$/metric ton)</b>						
Corn	140.772	178.317(26.67%)	177.48(26.08%)	141.402(0.45%)	178.32(26.67%)	199.406(41.65%)
Soybean	317.229	391.676(23.47%)	389.159(22.67%)	317.782(0.17%)	390.238(23.01%)	442.917(39.62%)
Wheat	226.007	238.284(5.43%)	237.225(4.96%)	227.304(0.57%)	239.385(5.92%)	238.966(5.73%)
Sorghum	108.533	84.043(-22.56%)	67.897(-37.44%)	107.71(-0.76%)	67.956(-37.39%)	124.047(14.29%)
<b>Opportunity Costs (\$billions)</b>						
Opportunity Costs		6.95	7.10	0.04	7.19	8.10

Notes: This table presents the commodity prices and changes in consumer and producer surplus relative to baseline. The opportunity cost includes consumer and producer losses from decreases in the supply and increases in prices of affected major commodities. Percentages in parenthesis show changes in each of the five scenarios relative to the baseline. Prices go up for all commodities except for sorghum in Gulf-45, Gulf 45-R, Bay-25, and Gulf-45\_Bay-25-R scenarios. However, all prices increase in Gulf-45\_Bay-25-NL.

**Table 2. N Use and loading**

	<b>Baseline</b>	<b>Gulf-45</b>	<b>Gulf-45-R</b>	<b>Bay-25</b>	<b>Gulf-45_Bay-25-R</b>	<b>Gulf-45_Bay-25-NL</b>
<b>MARB N use and loading</b>						
N applied within the MARB (1000 metric tons)	6399.2	5018.5(-21.58%)	5006.6(-21.76%)	6413.7(0.23%)	5015.0(-21.63%)	5086.3(-20.52%)
<b>CBW N use and loading</b>						
N applied within the CBW (1000 metric tons)	310.17	328.11(5.78%)	315.57(1.74%)	230.5(-25.69%)	243.76(-21.33%)	245.25(-21.01%)
<b>MRW N use and loading</b>						
N applied within the MRW (1000 metric tons)	188.93	208.18(10.19%)	194.38(2.88%)	193(2.15%)	195.91(3.74%)	200.09(5.86%)
N delivered to Lake Erie (metric ton)	3420.9	3609.9(5.52%)	3420.9(0%)	3467.5(1.36%)	3420.9(0%)	3420.9(0%)

**Table 3. Land Use**

	<b>Baseline</b>	<b>Gulf-45</b>	<b>Gulf-45-R</b>	<b>Bay-25</b>	<b>Gulf-45_Bay-25-R</b>	<b>Gulf-45_Bay-25-NL</b>
<b>A: US land use (million hectares)</b>						
Corn	39.687	40.04(0.89%)	40.277(1.49%)	39.663(-0.06%)	40.236(1.38%)	37.296(-6.02%)
Soybean	38.157	36.249(-5%)	36.455(-4.46%)	38.139(-0.05%)	36.403(-4.6%)	34.1(-10.63%)
Wheat	11.997	11.96(-0.31%)	11.984(-0.11%)	11.991(-0.05%)	12.014(0.14%)	12.296(2.49%)
Sorghum	2.355	2.407(2.21%)	2.562(8.79%)	2.358(0.13%)	2.564(8.87%)	2.363(0.34%)
<b>B: MARB land use (million hectares)</b>						
Corn	31.38	28.456(-9.32%)	28.445(-9.35%)	31.461(0.26%)	28.463(-9.3%)	28.944(-7.76%)
Soybean	27.984	23.742(-15.16%)	23.722(-15.23%)	27.987(0.01%)	23.708(-15.28%)	23.972(-14.34%)
Wheat	6.679	6.855(2.64%)	6.759(1.2%)	6.671(-0.12%)	6.805(1.89%)	7.071(5.87%)
Sorghum	1.588	1.419(-10.64%)	1.365(-14.04%)	1.573(-0.94%)	1.367(-13.92%)	1.596(0.5%)
<b>C: CBW land use (million hectares)</b>						
Corn	1.057	1.118(5.77%)	1.119(5.87%)	0.903(-14.57%)	1.05(-0.66%)	1.082(2.37%)
Soybean	0.819	0.8162(-0.34%)	0.714(-12.82%)	0.778(-5.01%)	0.79(-3.54%)	0.792(-3.3%)
Wheat	0.358	0.339(-5.31%)	0.337(-5.87%)	0.315(-12.01%)	0.291(-18.72%)	0.272(-24.02%)
<b>D: MRW land use (million hectares)</b>						
Corn	0.719	0.733(1.95%)	0.729(1.39%)	0.719(0%)	0.733(1.95%)	0.74(2.92%)
Soybean	0.968	0.952(-1.65%)	0.964(-0.41%)	0.968(0%)	0.952(-1.65%)	0.951(-1.76%)
Wheat	0.159	0.162(1.89%)	0.154(-3.14%)	0.159(0%)	0.162(1.89%)	0.152(-4.4%)
<b>E: ROC land use (million hectares)</b>						
Corn	6.531	9.733(49.03%)	9.987(52.92%)	6.58(0.75%)	9.991(52.98%)	6.531(0%)
Soybean	8.385	10.739(28.07%)	10.956(30.66%)	8.406(0.25%)	10.952(30.61%)	8.385(0%)
Wheat	4.801	4.603(-4.12%)	4.735(-1.37%)	4.847(0.96%)	4.755(-0.96%)	4.801(0%)
Sorghum	0.768	0.988(28.65%)	1.197(55.86%)	0.784(2.08%)	1.196(55.73%)	0.768(0%)

**Table 4. Crop Production.**

	<b>Baseline</b>	<b>Gulf-45</b>	<b>Gulf-45-R</b>	<b>Bay-25</b>	<b>Gulf-45_Bay-25-R</b>	<b>Gulf-45_Bay-25-NL</b>
<b>A: US production (million metric tons)</b>						
Corn	381.2	353.04(-7.39%)	353.67(-7.22%)	380.72(-0.13%)	353.04(-7.39%)	337.23(-11.53%)
Soybean	120.09	111.81(-6.89%)	112.08(-6.67%)	120.02(-0.06%)	111.96(-6.77%)	106.11(-11.64%)
Wheat	29.9	29.179(-2.41%)	29.24(-2.21%)	29.82(-0.27%)	29.11(-2.64%)	29.132(-2.57%)
Sorghum	9.47	10.05(6.12%)	10.44(10.24%)	9.49(0.21%)	10.44(10.24%)	9.1(-3.91%)
<b>B: MARB production (million metric tons)</b>						
Corn	326.14	279.62(-14.26%)	279.71(-14.24%)	326.85(0.22%)	279.87(-14.19%)	282.13(-13.49%)
Soybean	90.101	75.897(-15.76%)	75.806(-15.87%)	90.046(-0.06%)	75.752(-15.93%)	76.224(-15.4%)
Wheat	12.74	12.395(-2.71%)	12.234(-3.97%)	12.733(-0.05%)	12.332(-3.2%)	12.481(-2.03%)
Sorghum	6.482	5.389(-16.86%)	5.168(-20.27%)	6.419(-0.97%)	5.168(-20.27%)	6.112(-5.71%)
<b>C: CBW production (million metric tons)</b>						
Corn	8.893	9.407(5.78%)	9.33(4.91%)	7.406(-16.72%)	8.466(-4.8%)	8.673(-2.47%)
Soybean	2.155	2.137(-0.84%)	2.133(-1.02%)	2.086(-3.2%)	2.107(-2.23%)	2.112(-2%)
Wheat	1.303	1.239(-4.91%)	1.231(-5.53%)	1.131(-13.2%)	0.914(-29.85%)	0.824(-36.76%)
<b>D: MRW production (million metric tons)</b>						
Corn	7.708	7.963(3.31%)	7.825(1.52%)	7.737(0.38%)	8.466(9.83%)	7.971(3.41%)
Soybean	3.502	3.448(-1.54%)	3.485(-0.49%)	3.502(0%)	2.107(-39.83%)	3.442(-1.71%)
Wheat	0.681	0.693(1.76%)	0.656(-3.67%)	0.681(0%)	0.914(34.29%)	0.651(-4.41%)
<b>E: ROC production (million metric tons)</b>						
Corn	38.46	56.052(45.74%)	56.807(47.7%)	38.73(0.7%)	56.827(47.76%)	38.46(0%)
Soybean	24.332	30.329(24.65%)	30.659(26%)	24.39(0.24%)	30.654(25.98%)	24.332(0%)
Wheat	15.176	14.853(-2.13%)	15.118(-0.38%)	15.275(0.65%)	15.171(-0.03%)	15.176(0%)
Sorghum	2.988	4.661(55.99%)	5.272(76.44%)	3.071(2.78%)	5.272(76.44%)	2.988(0%)

## Appendix

### 1.1 Gulf of Mexico, Chesapeake Bay, and Western Lake Erie

The annual hypoxic zone in the northern Gulf of Mexico is one of the largest in the world, and MARB is the largest drainage basin in the US (Aulenbach et al., 2007). It includes the Upper Mississippi River Basin (UMRB), Lower Mississippi River Basin (LMRB), Missouri River Basin (MRRB), Arkansas-White-Red River Basin (ARB), and Ohio-Tennessee River Basin (OTRB). Agriculture in MARB represents 70% of US cropland and accounts for between 50% (CENR, 2000) and 76% (David et al., 2010) of the N delivery to the Gulf (Metaxoglou & Smith, 2023). USGS estimates that about 90% of N entering the Gulf originates from the OTRB and UMRB (Goolsby et al., 1999). Hence, these sub-basins require more attention for reducing nitrogen runoff than other regions (Kling et al., 2014). Despite the Mississippi River/Gulf of Mexico Hypoxia Task Force, which was initiated in 1997, the hypoxic zone grew from 16,670 km<sup>2</sup> in 2015 to 22,720 km<sup>2</sup> in 2017 (USEPA, 2021; Khanna et al., 2019). The task force's objective is to reduce the dead zone to 5,000 km<sup>2</sup>, which requires at least 45% N and P reduction from MARB (USEPA, 2008; Robertson & Saad, 2013).

Numerous studies have examined hypoxia in the Gulf, N export, and best management practices to reduce cropland nutrient runoff (Kling et al., 2014; Rabotyagov et al., 2014; Rabotyagov et al., 2010; Robertson et al., 2019; White et al., 2014; Xu et al., 2022). However, the implications of Gulf N loading reduction for N deliveries to other downstream coastal ecosystems, like the Chesapeake Bay and Western Lake Erie, have yet to be examined.

The Chesapeake Bay receives nutrients from a 165,000 km<sup>2</sup> watershed spanning six states and the District of Columbia with about 15 million people and is susceptible to eutrophication and hypoxia

due to anthropogenic activities (Kemp et al., 2015; Boesch et al., 2001; Du et al., 2018). Approximately \$2 billion had been spent as of 2017 on the Bay restoration activities (Kleinman et al., 2019). Over a decade ago, the USEPA collaborated with states in the Chesapeake Bay watershed to implement Total Maximum Daily Load (TMDL) for N, P, and sediment in each tributary draining into the Bay (USEPA, 2017). The TMDL was developed due to inadequate progress and low water quality in the Chesapeake Bay and restricts annual N and P loadings to 84.3 million kg (185.9 million lbs.) and 5.7 million kg (12.5 million lbs.), respectively. Agricultural production contributes over 50% of N loading in the Bay (Boyer et al., 2002). Although dissolved oxygen in Chesapeake Bay has improved, reducing nonpoint pollution from agricultural production remains a significant challenge (Kleinman et al., 2019; Zhang et al., 2018). Therefore, reducing agricultural nutrient loadings via best management practices remains a major point of interest for water quality in the Chesapeake Bay TMDL (Bosch et al., 2018).

MRW is the largest drainage system in the Great Lakes region and discharges the most nutrient and sediment loads into the Western Basin of Lake Erie, contributing to the toxic algal blooms (Cousino et al., 2015; Liu et al., 2020; Scavia et al., 2017). The watershed includes 17,000 km<sup>2</sup> in three states (northwestern Ohio, northeastern Indiana, and southern Michigan). Eighty-five percent of P loadings in MRW come from agriculture (Liu et al., 2020). The United States (US) and Canada signed the Great Lakes Water Quality Agreement (GLWQA) in 1972 to reduce total P loading to the Great Lakes (IJC, 1978). In 1987, the USEPA identified the 2007 km<sup>2</sup> of the MRW as an Area of Concern (AOC) due to agricultural nonpoint pollution (Cousino et al., 2015; US EPA, 2013). While P is the primary contributor to Lake Erie eutrophication, excessive N loadings in late summer can exacerbate the algal bloom (US EPA, 2017; Liu et al., 2020; Scavia et al., 2017). Therefore, avoiding or reducing N delivery to Western Lake Erie is an important element of improving water quality in the bay. Lake Erie's western basin has been listed as impaired under section 303(d) of the Clean Water Act, in 2016,

2018, and 2020 due to nutrient loadings and algae growth. As a result, a proposed consent decree in a lawsuit (Environmental Law & Policy Center et al., v. United States Environmental Protection Agency, No. 3:19-cv-295 (ND Ohio)) requests Ohio to prepare a draft TMDL for the Maumee River Watershed (Maumee Watershed Nutrient TMDL) to address the nutrient and algae impairments for drinking water, aquatic life, and recreational uses in Ohio's Western Lake Erie (USEPA, 2022).

## ***1.2 IHEAL Model***

The IHEAL model maximizes the producer and consumer surplus in four major commodity markets, including corn, soybean, wheat and sorghum. Other commodities are cumulatively included in the model as part of county scale land use constraints (Chen and Önal, 2012; Chen et al., 2014). The choice variables are national supply, demand, and county-scale production decisions, including crop planting acreages and corresponding per-acre N use and irrigation. The constraints include commodity-specific supply-demand balance with exports and imports, and land allocation as a convex combination of historically observed and synthetic county crop acreages. Detailed discussion is in the appendix 1.2 and 1.3.

Xu et al. (2022) use IHEAL to evaluate the relationship between N loading in the Gulf of Mexico and energy and fertilizer prices. We extend Xu et al. (2022) by including the MRW and CBW to quantify the potential relocation of coastal N loading from more to less regulated watersheds. We explicitly model MRW and CBW using crop specific nutrient runoff and production functions. The eight-digit watershed (HUC8) “edge of field” nutrient runoff and yield estimates are obtained from the SWAT-based Hydrologic and Water Quality System (HAWQS).

The objective function (Equation 1) maximizes the sum of consumer and producer surplus (Xu et al., 2022) with county scale planted acreage, N use, irrigation, aggregate supply and demand as endogenous variables.

$$\max_{X, L} \sum_c \int_0^{x_c^d} p_c^d (X_c^d, \omega_c) dX_c^d - \sum_{c,i,n} tc_{ci} * L_{cinw} - \sum_{c,i} FC_{ci} - \sum_{c,i} WC_{ci} \quad (1)$$

where,  $P_c^d (X_c^d, \omega_c)$  is the national inverse demand function for crop  $c$  and  $X_c^d$  is aggregate demand.  $\omega_c$  is the corresponding demand shifter.  $tc_{ci}$  is production cost per ha excluding N fertilizer use for crop  $c$  in county  $i$ ,  $L_{cinw}$  is the acreage of crop  $c$  in county  $i$  with  $n$  kg N fertilizer application and  $w$  water use.  $FC_{ci}$  and  $WC_{ci}$  are the N fertilizer and water costs for crop  $c$  in county  $i$ .

Four major commodities, including corn, soybean, wheat and sorghum are explicitly included to model N runoff and loading while other crops are included in land use rotation constraints. Corn, wheat, and sorghum are some of the most N intensive major agricultural commodities produced in the US, while soybean is often planted in rotation with corn. Within MARB, corn, soybean, and sorghum yields depend on per acre N use and irrigation, while wheat depends only on N use. In CBW and MRW, corn, soybean, and wheat depend on N use. No irrigation is used, and no sorghum is produced in CBW and MRW. The commodities explicitly modeled in this study represent more than 90% of major crop acreages in each of the three watersheds and are most relevant for nitrogen runoff (Xu et al. 2022).

The model is constrained as follows:

$$X_c^d + exports \leq X_{ci}^s + imports \quad \forall c, \quad (2)$$

$$\sum_{n,w} \gamma_{cinw} * L_{cinw} \geq X_{ci}^s \quad \forall c, i, \quad (3)$$

$$FC_{ci} = \sum_{n,w} \theta_{cin} * L_{cinw} \quad \forall c, i, \quad (4)$$

$$WC_{ci} = \sum_{n,w} \mu_{ciw} * L_{cinw} \quad \forall c, i, \quad (5)$$

$$\sum_n L_{cinw} = \sum_m \tau_{mi} * h_{cim} + \sum_v \gamma_{vi} * s_{civ} \quad \forall c, i, \quad (6)$$

$$\sum_m \tau_{mi} + \sum_v \gamma_{vi} = 1 \quad \forall i, \quad (7)$$

$$NR_k = \sum_i^{I \in k} (dr_{i,k} * \sum_{c,n,w} nrf_{cinw} * L_{cinw}) \quad \forall k \quad (8)$$

Equation 2 balances the supply and demand for each commodity, where total demand for crop  $c$  cannot exceed total supply. Equation 3 shows that the supply of crop  $c$  from county  $i$  cannot be greater than the production, where  $y_{cinw}$  denotes yield of crop  $c$  per ha in county  $i$  as a function of fertilizer use  $n$ , and water use  $w$ . The yield functions are obtained using HAWQS in terms of discrete nitrogen use per acre.  $n$  includes four nitrogen use values ranging from no nitrogen fertilizer to yield-maximizing use according to HAWQS, which provides these estimates at the hydrologic unit scale. Equation 4 estimates N fertilizer costs for crop  $c$  in county  $i$ , where  $\theta_{cin}$  is the N fertilizer per ha cost for each fertilizer application scenario  $n$ . Equation 5 estimates water costs for crop  $c$  in county  $i$  and irrigation schedule  $w$ , where  $\mu_{ciw}$  is the per ha water cost.

Equation 6 restricts land allocation to crop  $c$  in county  $i$ . County acreage of crop  $c$  is the weighted sum of historical and synthetic crop mix acreages. The indexes  $m$  and  $v$  are historical and synthetic crop mixes, respectively (Chen & Önal, 2012);  $h_{cim}$  and  $s_{civ}$  are  $m^{th}$  and  $v^{th}$  county-specific historical and synthetic acreage data of crop  $c$  in county  $i$ , respectively;  $\tau_{mi}$  and  $\gamma_{vi}$  are the endogenously estimated convex combination weights for historical and synthetic crop acreages. This formulation expresses the estimated allocation of land ( $L_{cinw}$ ) for crop  $c$  in county  $i$  with fertilizer and

irrigation use schedules  $n$  and  $w$ , in terms of convex combinations of acreages observed in the past and synthetically simulated acreages.

We follow Chen & Önal (2012) to obtain synthetic crop mixes from own & cross-price acreage and own & cross-lagged acreage elasticities. These elasticities are estimated from county production and price data from 2005 to 2019 using the fixed effect Arellano-Bond estimator (Xu et al., 2022). Synthetic crop mixes are generated using planted acreages observed in the past and cross crop acreage elasticities. After estimating the Arellano-Bond regressions, crop prices are systematically varied to obtain synthetic crop acreages across price scenarios. The inclusion of synthetic and observed crop acreage mixes adds flexibility to the model in terms of crop planting acreage solutions relative to relying solely on convex combination of only the observed acreages in the past.

Equation 7 restricts the sum of endogenous crop mix weights,  $\tau_{mi}$  and  $\gamma_{vi}$  to equal 1, which ensures that the optimal county crop acreages are convex combinations of acreages observed in the past years and acreages simulated synthetically. As such, estimated crop acreage ( $L_{cinw}$ ) is bounded by historically observed planting that is used either directly ( $h_{cim}$ ) or indirectly via synthetic acreages ( $s_{civ}$ ) that are estimated using past acreages and prices.

Equation 8 estimates N deliveries to each of the three coastal areas ( $k$ ) using delivery ratios ( $dr_{i,k}$ ) from county  $i$  to outlet  $k$ .  $nrf_{cinw}$  is the per-ha N runoff from planting crop  $c$  with fertilizer use  $n$  and irrigation  $w$  in county  $i$ .

Production activities in only MARB, CBW, and MWR are integrated with SWAT elements, including corresponding delivery ratios to obtain the downstream N loading. However, land use in the ROC is included in IHEAL only to account for aggregate production activities influencing national

supply estimates and commodity prices. All counties in the contiguous US where corn, soybean, wheat, or sorghum was produced in at least one year from 2005 to 2019 are included in IHEAL.

Crop prices and county acreages from 2005 to 2019 are obtained from USDA NASS (2020). Fertilizer, water, and other production costs come from USDA ERS (USDA ERS, 2019). Commodity demand elasticities are obtained from previous literature and are -0.28, -0.29, -0.34, and -0.3 for Corn, Soybean, Wheat, and Sorghum, respectively (Ishida & Jaime, 2015; Piggott & Wohlgenant, 2002; Westcott & Hoffman, 1999).

### ***1.3 SWAT/HAWQS Simulations.***

SWAT is a widely used semi-distributed hydrologic watershed quality model that incorporates weather, soil, land cover, and management parameters to quantify the environmental and productivity impacts of various production practices (Abbaspour et al., 2015; Arnold et al., 2012; Gebremariam et al., 2014; Liu et al., 2019; Wagena & Easton, 2018). SWAT is a process-based model that predicts hydrology, sediment and chemical fluxes using weather, soil, land cover and management data (Arnold et al., 1998). The advantage of SWAT is that it supports a scenario-based assessment of management practices and their environmental and productivity impacts. The SWAT-based Hydrologic and Water Quality System (HAWQS) online platform is used to obtain eight-digit watershed (HUC8) scale estimates for crop yields and N leaching as a function of per acre N fertilizer use (HAWQS, 2020). We simulate N surplus and crop yields for various levels of per-acre fertilizer application. The simulation periods cover 1999 to 2018. N use and loadings are estimated for corn at 50, 100, 150, 200, 250, and 300 lbs./acre, for sorghum at 50, 100, 150, and 200 lbs./acre, for wheat at 50, 75, 100 and 125 lbs./acre, and for soybean at 5, 10, and 15 lbs./acre.

Each watershed in HAWQS is divided into HUC8s based on land use, soil type, and slope characteristics. There are 822, 54, and 7 HUC8 sub-basins in MARB, CBW and MRW, respectively. We transform the HAWQS HUC8 scale estimates for N leaching and yields to county scale data using area weighted averages because IHEAL is developed using counties as a special unit. The land use model includes 1,590, 157, 24, and 1,017 counties in MARB, CBW, MRW and ROC respectively

County-scale land use and N leaching is linked with SWAT delivery ratios to obtain N loading in the Gulf of Mexico, the Chesapeake Bay, and Western Lake Erie. The delivery ratios are obtained from White et al. (2014), Chesapeake Bay Program (2020), and NRCS (2017) for MARB, CBW, and MRW, respectively. The original delivery ratios are at HUC8 scale and are converted to county scale parameters using area weighted average transformation.

#### **1.4 Model Validation and Baseline Results**

Validation results demonstrate model reliability (*see Supplementary Tables A1 and A2*), while baseline results serve as a reference point for the policy scenario analyses. The baseline year for model validation is 2018. The model is calibrated to produce the best possible replication of the observed land use and market data in the business-as-usual setting without the restrictions on N deliveries. The model with synthetic and historical crop acreages is used to produce five N loading reduction scenario results, which are evaluated relative to the baseline results with no restrictions on N loading.

The solutions in the validation column are based on crop acreage constraints that reflect historical annual crop mixes. Baseline solutions include synthetic and historical crop mix data. Synthetic crop acreages are added to provide greater model flexibility than the specification with only the historical crop mix. The additional flexibility is advantageous for analyzing scenarios where

scenario constraints or parameter values differ significantly from the historically observed settings (Chen & Önal, 2012; Xu et al., 2022).

Validation results for crop prices and acreages in panels A and B are similar to Xu et al. (2022)<sup>1</sup> and are within 4% and 16% of the observed values in 2018. Hence, the validation solutions support using the model for policy scenario analysis. It is also reassuring that baseline results with synthetic crop acreage specification are reasonably close to the observed data.

Panels C, D, E, and F provide disaggregated land use estimates for three focus watersheds and the rest of the country (ROC). In most cases, corn, soybean, wheat, and sorghum acreages are slightly greater than the values observed in 2018. In MARB, land use is within 10% of the observed values. Corn, soybean, and wheat acreages in CBW (MRW) deviate from the observed values by 11%, 16%, and 107% (3%, -0.4%, and 21%), respectively. Although the wheat acreage percent deviations in CVW and MRW appear to be large, in absolute terms, the overestimation is insignificant because baseline wheat acreages in these regions are very small. Overall, the upward marginal bias of acreages for these crops is observed because the objective function explicitly includes consumer and producer surplus measures only for these four commodities. Other commodities, and associated benefits, are not included in the objective function and are instead collectively included in the model as part of the crop acreage convexity constraints. As a result, the four commodities are slightly overproduced, and the corresponding prices are slightly lower than observed in 2018. However, the bias is insignificant in absolute terms and is unlikely to have a significant systematic impact on the assessment of N leakage across watersheds relative to the baseline scenario, which is the main objective of this study.

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<sup>1</sup> Some differences are observed for production and acreage in ROC because in Xu et al. (2022) MRW and CBW are included in ROC, while in this study these regions are modeled separately. In addition, unlike Xu et al. production activities in MWR and CBW are expressed as functions of N rather than using fixed average per acre yield.

*Supplementary, Table A2* shows validation results, baseline solutions, and estimates from the literature or data from USDA NASS (2019) for N use and delivery. N use in MARB is 6,692 thousand metric tons, approximately 53% of N use in the contiguous US. The corresponding N delivery to the Gulf of Mexico from corn, soybean, wheat, and sorghum production in MARB is 361.6 thousand metric tons, which is approximately 88% of the annual loading in the Gulf from agricultural production (White et al., 2014; Elbakidze et al., 2022). Similarly, our baseline estimates for N runoff to the Chesapeake Bay and Lake Erie are 21.97 and 3.39 thousand metric tons, respectively. N delivery to the Chesapeake Bay is 55% of agricultural loading in Ator et al. (2020). Chang et al. (2021) estimate the 2017 N loads to non-tidal CBW at 52 thousand metric tons from all sources, including legacy N. Our N loading estimate for MRW is about 5% of the cumulative agricultural delivery from US and Canadian drainages to Lake Erie (Robertson et al., 2019).

**Table A1. Validation and Baseline Results for Land Use and Prices**

	Validation results	Baseline results	Observed data <sup>2,3</sup>
<b>A. Prices (\$/metric ton)</b>			
Corn	138.159	140.772	142
Soybean	307.444	317.229	314
Wheat	181.514	226.007	190
Sorghum	113.312	108.533	117
<b>B. Land use (million hectares) for the contiguous US.</b>			
Corn	40.426	39.687	36
Soybean	39.148	38.157	36.1
Wheat	15.369	11.997	13.27
Sorghum	2.425	2.355	2.3
<b>C. Land use (million hectares) in MARB</b>			
Corn	32.079	31.38	30.247
Soybean	28.859	27.984	30.145
Wheat	10.197	6.679	11.116
Sorghum	1.765	1.588	1.903
<b>D. Land use (million hectares) in CBW</b>			
Corn	1.072	1.057	0.962
Soybean	0.816	0.819	0.703
Wheat	0.337	0.358	0.163
<b>E. Land use (million hectares) in MRW</b>			
Corn	0.711	0.719	0.689
Soybean	0.984	0.968	0.988
Wheat	0.143	0.159	0.118
<b>F. Land use (million hectares) ROC</b>			
Corn	6.564	6.531	9.634
Soybean	8.489	8.385	9.104
Wheat	4.692	4.801	3.359
Sorghum	0.66	0.768	1.9

<sup>2</sup> Source: USDA NASS, 2019

<sup>3</sup> 2018 is used for validation because commodity demand functions are calibrated using 2018 data.

**Table A2. Validation and Baseline Results for N Use and N Loading**

	Validation results	Baseline results	Values from the literature
<b>MARB</b>			
N applied within the MARB (1,000 metric tons)	6,692	6,399	12,610 (US) <sup>4</sup>
N delivered to the Gulf from fertilizer application (metric ton)	361,620	358,910	410,190 (MARB) <sup>5</sup>
<b>CBW</b>			
N applied within the CBW (1,000 metric tons)	309	310	12,610 (US)
N delivered to the Bay from fertilizer application (metric ton)	21,966	22,212	40,000 <sup>6</sup>
<b>MRW</b>			
N applied within the MRW (1,000 metric tons)	183	189	12,610 (US)
N delivered to Lake Erie from fertilizer application (metric ton)	3,386	3,421	67,425 <sup>7</sup>

<sup>4</sup> The sum of county-level farm N fertilizer use (Falcone, 2021).

<sup>5</sup> Source: White et al., 2014, N fertilizer use in crop production accounts for 68% of N delivered to the Gulf of Mexico from agriculture. The rest of N exported to the Gulf from agriculture comes from confined animal operations and legume crops (USGS, 2017).

<sup>6</sup> Source: Ator et al., 2020.

<sup>7</sup> Source: Robertson et al., (2019) which includes total loading in Lake Erie from US and Canada.

## References

Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology*, 524, 733–752. <https://doi.org/10.1016/j.jhydrol.2015.03.027>

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., & Neitsch, S. L. (2012.). *Input/Output Documentation Soil & Water Assessment Tool*.

Arnold, J.G., Srinivasan, R., Muttiah, R.R., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. *J. Am. Water Resour. Assoc.* 34 (1), 73–89

Ator, S. W., Blomquist, J. D., Webber, J. S., & Chanat, J. G. (2020). Factors driving nutrient trends in streams of the Chesapeake Bay Watershed. *Journal of Environmental Quality*, 49(4), 812–834. <https://doi.org/10.1002/jeq2.20101>

Aulenbach, B. T., Buxton, H. T., Battaglin, W. A., & Coupe, R. H. (2007). Streamflow and nutrient fluxes of the Mississippi-Atchafalaya River Basin and subbasins for the period of record through 2005. *Open-File Report*. <https://doi.org/10.3133/OFR20071080>

Boesch, D. F., Brinsfield, R. B., & Magnien, R. E. (2001). Chesapeake Bay Eutrophication: Scientific Understanding, Ecosystem Restoration, and Challenges for Agriculture. *Journal of Environmental Quality*, 30(2), 303–320. <https://doi.org/10.2134/jeq2001.302303X>

Bosch, D. J., Wagena, M. B., Ross, A. C., Collick, A. S., & Easton, Z. M. (2018). Meeting Water Quality Goals under Climate Change in Chesapeake Bay Watershed, USA. *Journal of the American Water Resources Association*, 54(6), 1239–1257. <https://doi.org/10.1111/1752-1688.12684>

Boyer, E. W., Goodale, C. L., Jaworski, N. A., & Howarth, R. W. (2002). Anthropogenic nitrogen sources and relationships to riverine nitrogen export in the northeastern USA. In *Biogeochemistry* (Vol. 57).

CENR. (2000). Integrated assessment of hypoxia in the northern Gulf of Mexico. National Science and Technology Council Committee on Environment and Natural Resources.

Chang, S. Y., Zhang, Q., Byrnes, D. K., Basu, N. B., & van Meter, K. J. (2021). Chesapeake legacies: The importance of legacy nitrogen to improving Chesapeake Bay water quality. *Environmental Research Letters*, 16(8). <https://doi.org/10.1088/1748-9326/ac0d7b>

Chen, X., Huang, H., Khanna, M., & Önal, H. (2014). Alternative transportation fuel standards: Welfare effects and climate benefits. *Journal of Environmental Economics and Management*, 67(3), 241-257

Chen, X., & Önal, H. (2012). Modeling Agricultural Supply Response Using Mathematical Programming and Crop Mixes. *American Journal of Agricultural Economics*, 94(3), 674–686. <https://doi.org/10.1093/AJAE/AAR143>

Chesapeake Bay Program, 2020. Chesapeake Assessment and Scenario Tool (CAST) Version 2019. Chesapeake Bay Program Office. Last accessed [July 2021] at <https://cast.chesapeakebay.net>

Cousino, L. K., Becker, R. H., & Zmijewski, K. A. (2015). Modeling the effects of climate change on water, sediment, and nutrient yields from the Maumee River watershed. *Journal of Hydrology: Regional Studies*, 4, 762–775. <https://doi.org/10.1016/j.ejrh.2015.06.017>

David, M. B., Drinkwater, L. E., & McIsaac, G. F. (2010). Sources of nitrate yields in the Mississippi River Basin. *Journal of environmental quality*, 39(5), 1657-1667

Du, J., Shen, J., Park, K., Wang, Y. P., & Yu, X. (2018). Worsened physical condition due to climate change contributes to the increasing hypoxia in Chesapeake Bay. *Science of the Total Environment*, 630, 707–717. <https://doi.org/10.1016/j.scitotenv.2018.02.265>

Elbakidze, L., Xu, Y., Gassman, P. W., Arnold, J. G., & Yen, H. (2022). Climate Change and Downstream Water Quality in Agricultural Production: The Case of Nutrient Runoff to the Gulf of Mexico. In American Agriculture, Water Resources, and Climate Change, Edited by G. Libecap and A. Dinar. NBER Chapters. DOI 10.3386/w30153, Available online <https://www.nber.org/papers/w30153>

Falcone, J. A. (2021). Estimates of county-level nitrogen and phosphorus from fertilizer and manure from 1950 through 2017 in the conterminous United States (No.2020-1153). In: US Geological Survey.

Gebremariam, S. Y., Martin, J. F., DeMarchi, C., Bosch, N. S., Confesor, R., & Ludsin, S. A. (2014). A comprehensive approach to evaluating watershed models for predicting river flow regimes critical to downstream ecosystem services. *Environmental Modelling and Software*, 61, 121–134. <https://doi.org/10.1016/J.ENVSOFT.2014.07.004>

Goolsby, D. A., Battaglin, W. A., Lawrence, G. B., Artz, R. S., Aulenbach, B. T., Hooper, R. P., Keeney, D. R., & Stensland, G. J. (1999). *Flux and Sources of Nutrients in the Mississippi-Atchafalaya River Basin Topic 3 Report for the Integrated Assessment on Hypoxia in the Gulf of Mexico*. <http://www.cop.noaa.gov>

HAWQS. (2020). *System and Data to model the lower 48 conterminous US using the SWAT model - HAWQS Dataverse*. <https://dataVERSE.tdl.org/dataset.xhtml?persistentId=doi:10.18738/T8/XN3TE0>

IJC. (1978). Great Lakes water quality agreement of 1978 with annexes and terms of reference, between the United States and Canada Signed at Ottawa, November 22, 1978. International Joint Commission, Windsor, ON

Kemp, W. M., Boynton, W. R., Adolf, J. E., Boesch, D. F., Boicourt, W. C., Brush, G., Cornwell, J. C., Fisher, T. R., Glibert, P. M., Hagy, J. D., Harding, L. W., Houde, E. D., Kimmel, D. G., Miller, W. D., Newell, R. I. E., Roman, M. R., Smith, E. M., & Stevenson, J. C. (2005). Eutrophication of Chesapeake Bay: historical trends and ecological interactions. *Marine Ecology Progress Series Mar Ecol Prog Ser*, 303, 1–29. www.int-res.com

Khanna, M., Gramig, B. M., Delucia, E. H., Cai, X., & Kumar, P. (2019). Harnessing emerging technologies to reduce Gulf hypoxia. *Nature Sustainability*, 2, 889–891. <https://doi.org/10.1038/s41893-019-0381-4>

Kleinman, P. J. A., Fanelli, R. M., Hirsch, R. M., Buda, A. R., Easton, Z. M., Wainger, L. A., Brosch, C., Lowenfish, M., Collick, A. S., Shirmohammadi, A., Boomer, K., Hubbart, J. A., Bryant, R. B., & Shenk, G. W. (2019). Phosphorus and the Chesapeake Bay: Lingering Issues and Emerging Concerns for Agriculture. *Journal of Environmental Quality*, 48(5), 1191–1203. <https://doi.org/10.2134/jeq2019.03.0112>

Kling, C. L., Panagopoulos, Y., Rabotyagov, S. S., Valcu, A. M., Gassman, P. W., Campbell, T., White, M. J., Arnold, J. G., Srinivasan, R., Jha, M. K., Richardson, J. J., Moskal, L. M., Turner, R. E., & Rabalais, N. N. (2014). LUMINATE: Linking agricultural land use, local water quality and Gulf of Mexico hypoxia. *European Review of Agricultural Economics*, 41(3), 431–459. <https://doi.org/10.1093/erae/jbu009>

Liu, Y., Wang, R., Guo, T., Engel, B. A., Flanagan, D. C., Lee, J. G., Li, S., Pijanowski, B. C., Collingsworth, P. D., & Wallace, C. W. (2019). Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. *Journal of Hydrology*, 577(July), 123965. <https://doi.org/10.1016/j.jhydrol.2019.123965>

Liu, H., Zhang, W., Irwin, E., Kast, J., Aloysius, N., Martin, J., & Kalcic, M. (2020). Best Management Practices and Nutrient Reduction: An Integrated Economic-Hydrologic Model

of the Western Lake Erie Basin. *Land Economics*, 96(4), 510–530. <https://doi.org/10.3386/wpl.96.4.510>

Metaxoglou, K., & Smith, A. (2023). “Nutrient pollution and US agriculture: Causal effects, integrated assessment, and implications of climate change.” In *Economic Perspectives on Water Resources, Climate Change, and Agricultural Sustainability*, edited by Ariel Dinar and Gary Libecap. National Bureau of Economic Research (NBER) and the University of Chicago. <https://www.nber.org/books-and-chapters/american-agriculture-water-resources-and-climate-change>

NRCS, 2017. Conservation Practice Adoption on Cultivated Cropland Acres: Effects on Instream Nutrient and Sediment Dynamics and Delivery in Western Lake Erie Basin, 2003-06 and 2012. Conservation Effects Assessment Project (CEAP), Cropland Special Study Report. Accessed 30<sup>th</sup> June 2022. Online at [https://www.nrcs.usda.gov/Internet/FSE\\_DOCUMENTS/nrcseprd1355824.pdf](https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcseprd1355824.pdf)

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P. W., Arnold, J., Kurkalova, L., Secchi, S., Feng, H., & Kling, C. L. (2010). Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. *Ecological Applications*, 20(6), 1542–1555. <https://doi.org/10.1890/08-0680.1>

Rabotyagov, S. S., Campbell, T. D., Marsha M., Arnold, J. G., Atwood, J., Norfleet, M. L., Kling, C. L., Gassman, P. W., Valcu, A., Richardson, J., Turner, R. E., & Rabalais, N. N. (2014). Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone. *Proceedings of the National Academy of Sciences of the United States of America*, 111(52), 18530–18535. <https://doi.org/10.1073/pnas.1405837111>

Robertson, D. M., & Saad, D. A. (2013). SPARROW models used to understand nutrient sources in the Mississippi/Atchafalaya River Basin. *Journal of Environmental Quality*, 42(5), 1422–1440.

Robertson, D. M., Saad, D. A., Benoy, G. A., Vouk, I., Schwarz, G. E., & Laitta, M. T. (2019). Phosphorus and Nitrogen Transport in the Binational Great Lakes Basin Estimated Using SPARROW Watershed Models. *Journal of the American Water Resources Association*, 55(6), 1401–1424. <https://doi.org/10.1111/1752-1688.12792>

Scavia, D., Kalcic, M., Muenich, R. L., Read, J., Aloysius, N., Bertani, I., Boles, C., Confesor, R., Depinto, J., Gildow, M., Martin, J., Redder, T., Robertson, D., Sowa, S., Wang, Y.-C., & Yen, H. (2017). Multiple models guide strategies for agricultural nutrient reductions. *Frontiers in Ecology and the Environment*, 15(3), 126–132. <https://doi.org/10.1002/fee.1472>

United States Environmental Protection Agency (USEPA), (2008). Gulf Hypoxia Action Plan [https://www.epa.gov/sites/default/files/2015-03/documents/2008\\_8\\_28\\_msbasin\\_ghap2008\\_update082608.pdf](https://www.epa.gov/sites/default/files/2015-03/documents/2008_8_28_msbasin_ghap2008_update082608.pdf)

United States Environmental Protection Agency (USEPA), (2013). “Maumee River”, Great Lakes Areas of Concern [http://www.epa.gov/greatlakes/aoc/maumee/index.html\(retrieved 26.01.15.\)](http://www.epa.gov/greatlakes/aoc/maumee/index.html(retrieved 26.01.15.))

United States Environmental Protection Agency (USEPA), (2017). Addressing nutrient pollution in the Chesapeake Bay. <https://www.epa.gov/nutrient-policy-data/addressing-nutrient-pollution-chesapeake-bay>. (Accessed 24 January 2022).

United States Environmental Protection Agency (USEPA), (2021). Mississippi River / Gulf of Mexico Hypoxia Task Force (Accessed 26 October 2022) Northern Gulf of Mexico Hypoxic Zone | Mississippi River/Gulf of Mexico Hypoxia Task Force | US EPA

United States Environmental Protection Agency (USEPA), (2022). Proposed Consent Decree: Clean Water Act and Administrative Procedure Act Claims by the EPA. *Regulations.gov* Accessed online November 14, 2022.

USDA NASS (United States Department of Agriculture National Agricultural Statistics Service). (2019). 2018 Irrigation and Water Management Data Now. available at <https://www.nass.USDA.gov/Newsroom/archive/2019/11-13-2019.php> (Accessed March 24, 2023)

USGS (United States Geological Survey) (2017). The Challenge of Tracking Nutrient Pollution 2,300 Miles (Accessed 6 Mar 2017) <https://www.usgs.gov/news/challenge-tracking-nutrient-pollution-2300-miles>.

Wagena, M. B., & Easton, Z. M. (2018). Agricultural conservation practices can help mitigate the impact of climate change. *Science of the Total Environment*, 635, 132–143. <https://doi.org/10.1016/j.scitotenv.2018.04.110>

White, M. J., Santhi, C., Kannan, N., Arnold, J. G., Harmel, D., Norfleet, L., Allen, P., DiLuzio, M., Wang, X., Atwood, J., Haney, E., & Johnson, M. V. (2014). Nutrient delivery from the Mississippi River to the Gulf of Mexico and effects of cropland conservation. *Journal of Soil and Water Conservation*, 69(1), 26–40. <https://doi.org/10.2489/jswc.69.1.26>

Xu, Y., Elbakidze, L., Yen, H., Arnold, J. G., Gassman, P. W., Hubbart, J., & Strager, M. P. (2022). Integrated assessment of nitrogen runoff to the Gulf of Mexico. *Resource and Energy Economics*, 67, 101279. <https://doi.org/10.1016/j.reseneeco.2021.101279>

Zhang, Q., Murphy, R. R., Tian, R., Forsyth, M. K., Trentacoste, E. M., Keisman, J., & Tango, P. J. (2018). Chesapeake Bay's water quality condition has been recovering: Insights from a multimetric indicator assessment of thirty years of tidal monitoring data. *Science of the Total Environment* 637-638, 1617-1625. <https://doi.org/10.1016/j.scitotenv.2018.05.025>