Water Quality Co-Benefits of Greenhouse Gas Reduction Incentives in U.S. Agriculture

Final Report

Prepared for

Benjamin DeAngelo, OAR/OAP/CPPD
U.S. Environmental Protection Agency
499 S. Capitol Street, SW
Washington, DC  20024

Prepared by

Subhrendu K. Pattanayak
Allan Sommer
Brian C. Murray
Timothy Bondelid
RTI
Health, Social, and Economics Research
Research Triangle Park, NC  27709

Bruce A. McCarl
Dhazn Gillig
Texas A & M University

EPA Contract Number 68-C-01-142
RTI Project Number 08249.001.004
Water Quality Co-Benefits of Greenhouse Gas Reduction Incentives in U.S. Agriculture

Final Report

September 4, 2002

Prepared for

Benjamin DeAngelo, OAR/OAP/CPPD
U.S. Environmental Protection Agency
499 S. Capitol Street, SW
Washington, DC  20024

Prepared by

Subhrendu K. Pattanayak
Allan Sommer
Brian C. Murray
Timothy Bondelid
RTI
Health, Social, and Economics Research
Research Triangle Park, NC  27709

Bruce A. McCarl
Dhazn Gillig
Texas A & M University
# Contents

**Executive Summary**

1. **Introduction**

2. **Model Components and Process Overview**
   - 2.1 ASMGHG ......................................................................... 2-1
   - 2.2 NWPCAM......................................................................... 2-2
     - 2.2.1 Water Quality Indices............................................ 2-4
   - 2.3 Model Process and Technical Approach for Evaluating GHG Policy Scenarios....................................................... 2-5

3. **Model Results**
   - 3.1 National-level Results........................................................ 3-1
     - 3.1.1 Economic Welfare Impacts........................................ 3-1
     - 3.1.2 GHG Mitigation from all Modeled Activities ............ 3-3
     - 3.1.3 Agricultural Mitigation and Environmental Loadings............................................................. 3-4
     - 3.1.4 National Water Quality Results.......................... 3-4
   - 3.2 Regional Results................................................................ 3-8
     - 3.2.1 GHG Mitigation from Cropland Activities............. 3-8
     - 3.2.2 Pollutant Loadings ........................................... 3-9
     - 3.2.3 Regional Water Quality Results..................... 3-11
   - 3.3 Case Studies: Breadbasket and Gulf States....................... 3-12
     - 3.3.1 Co-Benefits Elasticity........................................... 3-12
     - 3.3.2 Visual Analysis of National Maps......................... 3-14
     - 3.3.3 Case-Study I: The Breadbasket ......................... 3-15
     - 3.3.4 Case-Study II: The Gulf States....................... 3-17
4. Discussion

4.1 Water Quality Policy Context ............................................ 4-2
4.2 Explanations ..................................................................... 4-3
4.3 Qualifiers and Extensions .................................................. 4-5
4.4 Summary .......................................................................... 4-6

References .............................................................................. R-1
Figures

Figure 2-1  Model Process Overview ........................................................... 2-6
Figure 2-2  The NWPCAM Modeling System for Water Quality Co-
Benefits Due to GHG Mitigation Policies in LUCF ................. 2-9

Figure 3-1  Changes in Water Quality Indices (WQI) by Reach:
$25/Tonne Scenario Compared to Baseline ....................... 3-6
Figure 3-2  Changes in Water Quality Indices (WQI) by Reach:
$50/Tonne Scenario Compared to Baseline ....................... 3-7
Figure 3-3  Changes in Water Quality Indices (WQI) by Reach in the
Breadbasket Case Study: $25/Tonne Scenario Compared to
Baseline................................................................. 3-16
Figure 3-4  Changes in Water Quality Indices (WQI) by Reach in the
Gulf States Case Study: $25/Tonne Scenario Compared to
Baseline................................................................. 3-18
### Tables

<table>
<thead>
<tr>
<th>Table 3-1</th>
<th>National Summary of Welfare, Agricultural, and Environmental Impacts under Three GHG Prices</th>
<th>3-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 3-2</td>
<td>Regional Water Quality Indices (WQI) Under the Baseline and Alternative GHG Pricing Scenarios</td>
<td>3-5</td>
</tr>
<tr>
<td>Table 3-3</td>
<td>Regional Definitions</td>
<td>3-8</td>
</tr>
<tr>
<td>Table 3-4</td>
<td>GHG (Sum of CO₂, CH₄, and N₂O) Results from Cropland by Census Region in MMTCE</td>
<td>3-9</td>
</tr>
<tr>
<td>Table 3-5</td>
<td>N, P, and TSS Loadings (Million Tons) from Cropland by Region</td>
<td>3-10</td>
</tr>
<tr>
<td>Table 3-6</td>
<td>Co-Benefit Elasticity by Region</td>
<td>3-14</td>
</tr>
<tr>
<td>Table 3-7</td>
<td>Reduction in Loadings (Tons per Year) to the Gulf of Mexico Under Alternative GHG Pricing Scenarios</td>
<td>3-19</td>
</tr>
</tbody>
</table>
Executive Summary

There is growing interest in the role that agriculture and forestry can play in reducing the potential impacts of climate change by mitigating greenhouse gas (GHG) emissions. However, much of the attention has focused on measuring the cost of GHG mitigation activities. Little quantitative research exists on the “co-effects” of agriculture and forestry on water quality and quantity, soil quality, soil erosion, biodiversity, and acidification. Missing or incomplete data on co-effects can excessively focus the policy debate on a potentially limited set of costs and benefits of terrestrial GHG mitigating activities. Regardless of the policy interest in a comprehensive cost-benefit analysis of GHG mitigation activities, quantitative data on co-effects can be important for designing GHG mitigation policies that at least would not generate negative co-effects. In an attempt to respond to these concerns, this study develops first-order national estimates of water quality co-effects of terrestrial GHG mitigation strategies by linking a national level water quality model to a national level agricultural sector model.

Terrestrial activities in agriculture and forestry can mitigate greenhouse gas (GHG) through (1) carbon sequestration, (2) reduction of GHG emissions from management practices, and (3) substitution of renewable biomass based products for materials and processes that generate GHG emissions through fossil fuel combustion. The land use practices that mitigate GHG have substantial overlap with practices that have historically been used to improve environmental quality. For instance, agricultural soil management practices to sequester carbon can reduce farm-generated nonpoint source pollution. As such, widespread GHG
mitigation practices should, all else equal, simultaneously yield co-benefits. But economic behavior and market processes are complex. Feedback effects from GHG reduction incentives could, in principle, induce secondary effects that diminish water quality (e.g., switching to crops with greater fertilizer requirements). So the net effect on water quality is an empirical issue requiring quantitative analysis.

The model used to simulate the consequences of GHG mitigation policies as they would affect the agriculture and forestry sectors includes the Agricultural Sector Model-Greenhouse Gas Version (ASMGHG, Schneider and McCarl, 2002). ASMGHG is a national-level model of the U.S. agricultural and forestry sectors, with linkages between the sectors through land markets. It includes detail on agricultural production, particularly with regard to practices that impact carbon sequestration, CO₂ emissions, and non-CO₂ GHG reporting strategy use in 63 U.S. regions. Results generated by ASMGHG are used as inputs to the National Water Pollution Control Assessment Model (NWPCAM: RTI, 2000a; RTI, 2000b). NWPCAM is a national-scale modeling system designed to simulate water quality at a macro scale and is specifically designed to evaluate various policies, such as effects of the Clean Water Act and proposed rules on nutrient loadings from Animal Feeding Operations. It predicts water quality at either a Reach File Version 1 (RF1) level of detail (~630,000 miles of rivers and streams), or at a Reach File Version 3 level (> 3 million miles of rivers and streams) of detail. Thus, we leverage separate significant efforts that U.S. EPA has invested in the development of models, and use them to investigate how GHG mitigation is related to water quality. We investigate the sensitivity of land markets to the introduction of a market price for GHG reduction, expressed as $ per tonne of carbon equivalent (CE). ASMGHG estimates baseline crop mix, land use, and the potential changes in their market equilibrium from market incentives, which here includes a GHG price. Baseline conditions in ASMGHG represent a world with no carbon market. ASMGHG predicts that GHG prices of $25/tonne and $50/tonne will cause 5.8 million and 12.5 million acres to convert from agricultural to forested lands nationwide under the two prices respectively, along with several alterations in tillage practices and crop mix. As a result of these changes ASMGHG estimates reductions in GHG emissions of 89.3 MMTCE and 156.3 MMTCE nationwide. In addition to
GHG mitigation results, the ASMGHG provides detailed data on economic and welfare impacts, regional crop mix, regional tillage practices, afforestation, grassland conversion and pollutant loadings in terms of releases of nitrogen, phosphorous, and eroded soil.

Using ASMGHG pollutant loadings as inputs, NWPCAM simulates impacts on national water quality induced by GHG mitigation policy. The output from NWPCAM is a water quality index (WQI) on a 1 to 100 scale, representing the relative impact and abundance of six pollutants in the modeled waters. The water quality co-benefits are highest in the “Breadbasket” (in absolute) and in the “Gulf States” (proportional to GHG reduction). The key results from NWPCAM are as follows:

- Nationwide average water quality increases 1.38 WQI points under both GHG pricing scenarios.
- Five regions, all roughly East of the 100th meridian (North Plains, South Plains, Lake States, Corn Belt and the Delta States) experienced the largest water quality improvements ranging from about 3 to 8 percent.
- “Breadbasket” states (Iowa, Kansas, Nebraska, and the Dakotas) experienced the largest change in water quality, nearly a 4-point WQI improvement.
- Gulf States (Texas, Oklahoma, Louisiana, Mississippi, and Arkansas) have the highest co-benefit elasticity, revealing the largest improvement in water quality proportional to the amount of GHG mitigation.
- Nitrogen loadings into the Gulf decrease by about 9 percent, whereas phosphorous loadings decrease by less than 1 percent.

Section 1251 of the Clean Water Act (1977) defines the goal of establishing “boatable and fishable” water quality conditions in the nation’s waters by 1985. However, The National Water Quality Inventory Report to Congress in 1998 reported that about 40 percent of the streams that were monitored by the EPA were not clean enough to be classified as fishable or swimmable. It is clear from these findings that the goals of the CWA have not been met, 13 years after the deadline was established. Our results show that climate change policies can move the nation’s waters—on average—from below swimmable to approximately swimmable levels. It is worth emphasizing that this is a national weighted average, and clearly specific reaches and rivers will not accomplish this water quality.
Looking specifically at regions, we know that 20 to 60 percent of the miles of rivers in the “Breadbasket” do not meet their water quality goals, i.e., do not fully support their aquatic use designation. Our analysis shows that agricultural practices in response to GHG incentives can result in a 5 to 8 percent increase in water quality in this region. Although we know the primary causes of water quality problems in this region and the predicted improvements, the regional goals and accomplishments are too generally worded for us to directly place our results in a regional policy context. We can only conclude that there will be a 5 to 8 percent improvement, but not whether these improvements will allow this region to meet its water goals for 100 percent of its rivers and streams.

With regards to the hypoxia problem in the Gulf of Mexico, we find that GHG mitigation activities could reduce annual nitrogen loadings up to 9 percent, or nearly one half, of the reduction goals established by the Watershed Nutrient Task Force in 1997. In the case of phosphorous, generally more of a problem in freshwaters systems, we find that GHG mitigation activities will insignificantly reduce loadings to the Gulf.

We find that there is considerable heterogeneity across regions and GHG incentive scenarios in terms of agricultural loadings and in-stream water quality. These heterogeneous results reflect at least three factors. First, differences in regional comparative advantage in agricultural production and GHG mitigation cause inter-regional shifts in production activities in response to the GHG incentives. Second, some activities that enhance GHG benefits have offsetting water quality costs. Third, a carbon price is a GHG incentive, not a loadings or WQ incentive, and thus may cause agricultural practices to change in ways that mitigate or increase GHGs.

We also find that the higher GHG price did not necessarily generate higher water quality improvements; that is, while the initial GHG reduction results in a significant improvement in the WQI, the larger GHG price improves water quality, but to a lesser degree than the initial impacts. Consider four explanations for this. First, the direct GHG mitigation effects diminish as we move from the lower to the higher GHG price, so it is not too surprising that the water quality effects diminish as well. Second, the actual commodity being purchased is a reduction in GHG, not water quality improvements. Third, agricultural lands (linked to ASMGHG) are just one among a
myriad set of point and nonpoint source loadings into the nation’s waters. Fourth at higher GHG incentive prices, more land is diverted from traditional agricultural production to biofuels, forests, and grasslands. The remaining crop land is farmed more intensively with increased inputs and this tends to moderate the water quality gains.

The Gulf States show the greatest synergies (highest co-benefit elasticities) because the rivers flowing into the Gulf are the receptacle for the country’s primary agricultural lands, being at the lowest point in the hydrologic network. These rivers accumulate the improvements in water quality in all upstream regions, including the main agricultural zones—Corn Belt and North and South Plains.

It is critical to review some qualifications to the analysis and results presented in this report. First, we must recognize the inherent traits of aggregated or macro models such as ASMGHG and NWPCAM that are built on an aggregation of micro-level elements or cells. Projections and outputs from these aggregated models are more accurate at the aggregate level than at the individual cell. This qualification suggests we can only obtain broad-scale (national and regional) first-order estimates of policy induced GHG and WQ changes. Second, there are factors outside these model results—such as increased carbon stocks, conversion of lands to grassland and increased reliance on biofuels—that may have important environmental consequences not addressed here (see Section 4 for details). Finally, insufficient disaggregated data on forestry and livestock forced us to exclude any GHG mitigation policy induced alterations in loadings from these activities in the NWPCAM analysis.

Although the study was successful in accomplishing its primary objectives, two areas warrant further attention in future research. First, it would be useful to evaluate how loadings from livestock manure and afforestation influence the overall water quality results. Second, it would be informative to monetize the co-effects. Monetized estimates would allow us to evaluate whether the benefits of water quality improvements sufficiently supplement GHG mitigation benefits to offset, or possibly outweigh, the public and private cost of carbon payments.
In summary, claims of extensive and prevalent co-benefits (e.g., quality of soil, water, air and wildlife habitat) of GHG mitigation policies have not been backed up by rigorous quantitative analyses. This study develops first order estimates of water quality co-benefits by linking ASMGHG—a national model that estimates changes in land use and management, GHG emissions, and pollutant loadings in response to GHG price incentives—with NWPCAM—another national scale model that estimates pollutant fate, transport, and decay in the nation’s waters resulting in overall impacts on water quality. Prices of $25 and $50 per tonne of carbon equivalent, induces changes in cropping, management (e.g., conventional to no-till agriculture) and land use (afforestation). The associated changes in agricultural loadings of nitrogen, phosphorus, and eroded soil allow us to predict national water quality (measured using a single index). We measure overall economic and ecological impacts of GHG mitigation policies in terms of changes in economic welfare, LULC, GHG emissions, and water quality. Specifically, we find that the most significant water quality improvements are found in the “Breadbasket” and Gulf States of the U.S. Our results show that GHG mitigation policies, which would cause 6–13 million acres to leave agriculture, can improve the nation’s waters quality by an average of 1.38 points on the water quality index. Additionally, GHG mitigation activities could reduce annual nitrogen loadings into the Gulf by up to one half of the reduction goals established by the Watershed Nutrient Task Force for solving the hypoxia problem.
1

Introduction

There is growing interest in the role that terrestrial activities in agriculture, land use change, and forestry can play in reducing the potential impacts of climate change by mitigating greenhouse gas (GHG) emissions (Watson et al., 2000). However, much of the attention has focused on measuring the cost of GHG mitigation activities (Matthews, O’Connor, and Plantiga, 2002). The Intergovernmental Panel on Climate Change (IPCC) Special Report on Land Use, Land-Use Change and Forestry suggests most land-use change and forestry (LUCF) practices for GHG mitigation would likely lead to broader environmental benefits, though there may be tradeoffs between GHG benefits and environmental quality in some cases (Watson et al., 2000). Little quantitative research exists on the “co-effects” of land uses, which mitigate GHGs, on water quality and quantity, soil quality, soil erosion, biodiversity, and acidification (Plantinga and Wu, forthcoming). Missing or incomplete data on co-effects can excessively focus the policy debate on a potentially limited set of costs and benefits of terrestrial GHG mitigating activities. Regardless of the policy interest in a comprehensive cost-benefit analysis of GHG mitigation activities, quantitative data on co-effects can be important for designing GHG mitigation policies that at least would not generate negative co-effects and for designing the appropriate role for government. In an attempt to respond to these concerns, this study develops first-order national estimates of water quality co-effects of terrestrial GHG mitigation strategies by linking a national level water quality model (NWPCAM) to a national level agricultural sector model (ASMGHG).

Terrestrial or biological carbon sequestration removes carbon dioxide (CO₂) from the atmosphere and stores it as carbon in
biomass and soils. Typical land-use or land management practices that preserve and enhance terrestrial carbon storage include switching from conventional to low- or no-till agriculture, converting agricultural and pasture land to forests, protecting forests, lengthening rotation periods of the timber-harvest cycle, and establishing riparian buffers with forests or other native vegetation. Other forms of GHG mitigation from agriculture include reductions in N₂O from fertilizer use and reductions in methane (CH₄) from livestock management.

The land-use and land management practices that sequester carbon have substantial overlap with practices that have historically been used to improve environmental quality by reducing farm-generated nonpoint source pollution. As such, widespread land-based GHG mitigation practices should, all else equal, simultaneously yield environmental co-benefits. But economic behavior and market processes are complex. Feedback effects from GHG reduction incentives could, in principle, induce secondary effects that diminish water quality (e.g., switching to crops with greater fertilizer requirements). So the net effect on water quality is an empirical issue requiring quantitative analysis.

This study represents a first attempt to better understand the synergies and possible tradeoffs between terrestrial GHG mitigation strategies and the nation’s water quality objectives by linking a national level water quality model (NWPCAM) to a national level agricultural and forest sector model (ASMGHG) to jointly analyze both the GHG reduction and water quality implications of GHG mitigation strategies in U.S. agriculture. The project leverages separate significant efforts that U.S. EPA has invested in the development of models to address distinct, but related, environmental problems. We proceed with an evaluation of policies targeted at GHG reductions and evaluate the water quality co-benefits. However, the problem, in essence, could be viewed in reverse. That is, policies aimed primarily at water quality improvements may provide GHG mitigation benefits. Regardless, they are co-effects.

This study uses models previously developed with EPA support and interaction. The model used to simulate mitigation policies in the agriculture and forestry sector is the Agricultural Sector Model-Greenhouse Gases (ASMGHG, Schneider and McCarl, 2002;
McCarl and Schneider, 2001; Schneider, 2000). ASMGHG is a national-level model of the U.S. agricultural and forestry sector, with linkages between the sectors through land markets.\(^1\) ASMGHG also considers international trade in agricultural products. It includes considerable detail on agricultural production, particularly with regard to practices that impact carbon sequestration, CO\(_2\) emissions, and non-CO\(_2\) greenhouse gases reporting strategy use in 63 U.S. regions.

The results generated by ASMGHG are then used as an input to the National Water Pollution Control Assessment Model (NWPCAM: RTI, 2000a; RTI, 2000b; Bingham et al., 2000). Developed by Research Triangle Institute (RTI), NWPCAM is a national-scale modeling system designed to simulate water quality and is specifically designed to evaluate various policies. In particular it was designed to examine the effects of policies such as the effects of the Clean Water Act and proposed rules on nutrient loadings from Animal Feeding Operations. This model can generate water quality estimates at either a Reach File Version 1 (RF1) level of detail (~630,000 miles of rivers and streams), or at a Reach File Version 3 level (>3 million miles of rivers and streams) of detail.\(^2\) This work assignment thus leverages prior efforts by EPA, especially work for the Office of Science and Technology, the Office of Wastewater Management (NWPCAM), and the Office of Atmospheric Programs (ASMGHG). A more detailed discussion of ASMGHG and NWPCAM can be found in section 2 of this report.

In this study, we investigate the sensitivity of land markets to agricultural and forestry mitigation efforts simulated by the introduction of a market price for GHG reduction, expressed as $ per tonne of carbon equivalent (CE). We investigate agricultural crop mix and land use sensitivity to the introduction of a market price for GHG reduction in ASMGHG. Using the results from ASMGHG as inputs, NWPCAM simulates national impacts on water quality of terrestrial GHG mitigation activities. The output from NWPCAM is a water quality index (WQI) on a 1 to 100 scale.

\(^1\)A related model, FASOM, also co-developed by Dr. McCarl, more explicitly links the agricultural and forest sectors. ASMGHG was used for this analysis because of its wider coverage of GHGs and higher level of spatial detail.

\(^2\)These reach files were designed by the US EPA Office of Water. Information on these and other national hydrologic information can be found at the following web-address—http://www.epa.gov/owowtr1/monitoring/rf/rfindex.html
representing the relative impact and abundance of six pollutants in the modeled waters. NWPCAM results at the national level predict water quality to improve from the baseline WQI of 68.6 to 69.9 under both GHG pricing alternatives. Regional results show the largest regional improvement is over three points on the WQI.

In the remaining sections, we provide a brief summary of the two modeling components, ASMGHG and NWPCAM. This background section (Section 2) is accompanied by a discussion of the technical approach, which links the two model components in order to jointly estimate reductions in GHG emissions and water quality co-benefits. This is followed by a discussion of results from the ASMGHG model runs in Section 3, corresponding NWPCAM results, and national GHG and water quality impacts resulting from changes in agricultural management practices and land use. The report develops case study regions where the synergies between climate and water quality objectives appear to be especially promising. We conclude in Section 4 with a discussion of the central findings and qualifications, and policy relevance.
The primary goal of this study is to measure the joint GHG mitigation and water quality effects of GHG incentives in agriculture and forestry. To do that, we link two separate modeling systems. This section provides a detailed description of the two component systems and the technical approach developed to link the two.

### 2.1 ASMGHG

This model has been developed based on past work by McCarl and associates as reported in McCarl and Schneider (2000) and Chang et al. (1992). Their work created the agricultural sector model ASM, a mathematical programming-based, price-endogenous representation of the agricultural sector (ASM—McCarl and Schneider, 2000; Chang et al., 1992). ASM has since been modified to include GHG accounting practices by Schneider (2000). The original model was also expanded to include forestry possibilities for carbon production by including data on land diversion, carbon production and economic value of forest products as generated from a forestry sector model, FASOM (Adams et al., 1996) using 30-year average results over the 2000-2029 period. These modifications and expansions lead to the creation of a greenhouse gas version of ASM now called ASMGHG. All remaining discussion refers to the ASMGHG model functions and components used in this study.

ASMGHG depicts production, consumption, and international trade in 63 U.S. regions of 22 traditional and 3 biofuel crops, 29 animal
products, and more than 60 processed agricultural products. ASMGHG simulates the market and trade equilibrium in agricultural markets of the U.S. and 28 major foreign trading partners. Domestic and foreign supply and demand conditions are considered, as are regional production conditions and resource endowments. The market equilibrium reveals commodity and factor prices, levels of domestic production, export and import quantities, GHG emissions management strategy adoption, resource usage, and environmental impact indicators. ASMGHG environmental impact output includes estimates of levels of greenhouse gas emission or absorption for carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O); surface, subsurface, and ground water pollution for nitrogen (N) and phosphorous (P); and soil erosion.

Generally, ASMGHG considers

- Carbon sequestration from increases in soil organic matter reduced tillage intensity and conversion of arable land to grassland and from tree planting
- Carbon offsets from biofuel production (ethanol, power plant feedstock via production of switchgrass, poplar, and willow)
- Methane emissions from enteric fermentation, livestock manure, and rice cultivation
- Methane savings from manure management changes
- Nitrous oxide emissions from fertilizer usage and livestock manure
- Direct carbon dioxide emissions from fossil fuel use (diesel, gasoline, natural gas, heating oil, liquefied petroleum gas) in tillage, harvesting, or irrigation water pumping as well as altered soil organic matter (cultivation of forested lands or grasslands)
- Indirect carbon dioxide emissions from fertilizer manufacturing
- Methane and nitrous oxide emission changes from biomass power plants

2.2 NWPCAM

The National Water Pollution Control Assessment Model (NWPCAM) combines spatial data with data on pollutant loadings to model transport, fate, and decay processes within the nation’s waters. Specifically, NWPCAM uses the U.S. Geological Survey (USGS) conterminous United States Land Cover Characteristics (LCC) Data Set (Version 2). The LCC data set defines 26 land-use
classifications that are defined at a square kilometer cell grid level in the LCC. The image used to assign land-cover cells to an RF3 reach has a pixel size of 8-bit (1 byte), representing an area of 1 km². The land-use coverage is then overlaid on the RF3 hydrologic routing framework to associate each land-use cell with a specific RF3 reach, watershed, and hydroregion. Each land-use cell is assigned to the nearest routed RF3 reach for subsequent drainage area, stream discharge, and hydrologic routing purposes. Loadings from these land use cells are then routed to their corresponding RF3 reach and routed through the national network via water quality modeling techniques.

The method used for estimating nonpoint source loadings for both nutrients and conventional pollutants in NWPCAM is based on an export coefficient model that is applied on a watershed level. Export coefficients are empirical, aggregated parameters that describe the loading of a given nutrient or pollutant in terms of mass per unit time per unit area. The specification of export coefficients requires estimates of both the unit loading and the area of land within a catchment described in terms of different types or classes of land use and/or land cover. Each of the land use types has its own unique export coefficient based on the typical type and level of nutrients originating from the given land use.

In this study, a modified version of NWPCAM is used to model in-stream concentrations of nitrogen (N), phosphorous (P), and erosion or total suspended solids (TSS). Although erosion and TSS are not exactly the same, erosion is used as a proxy for TSS and will be referred to as such throughout the remaining discussion. This version of NWPCAM uses the Reach File Version 1 (RF1) stream network and incorporates simplified first-order kinetics in-stream modeling. Changes in loadings or land use as a result of proposed policies, regulations, or other environmental or social factors will result in a change in the export coefficients allowing NWPCAM to model the impact of the changes.

In NWPCAM, total suspended solids are used as a surrogate indicator of water transparency to characterize recreational service flows provided by a water body. Low TSS concentrations are associated with a high degree of water clarity. High concentrations of TSS are generally associated with murky or turbid waters and are therefore important contributors to perceptions of poor water
quality. A simple net settling velocity was used to parameterize the interactions of particle size distributions with deposition and re-suspension. The revised universal soil loss equation (RUSLE) was used to amend the export coefficients used for TSS loadings on agricultural land-use cells (USDA, 1997). NWPCAM’s nitrogen and phosphorous loadings were computed by land-use type and by ecoregion based on SPARROW (SPAtially Referenced Regression On Watershed attributes), which is a statistical modeling approach for estimating major nutrient source loadings at a reach scale based on spatially referenced watershed attribute data. This had the advantage of developing estimates of export coefficients that were spatially variable.

2.2.1 Water Quality Indices

Results from NWPCAM are presented using a water quality index (WQI) designed to incorporate the impact of the modeled pollutants on overall water quality. This index was created through the following steps and is based on past water quality valuation studies and advancements in NWPCAM.

Concentrations of pollutants are first estimated in NWPCAM under baseline and alternative policy scenarios. These concentrations are then converted to a continuous WQI based on individual nutrient measures. This second step is based on McClelland (1974), who developed a continuous composite WQI index based on nine individual measures of water quality. These nine water quality indicators are biological oxygen demand (BOD), dissolved oxygen (DO), fecal coliform bacteria (FCB), total suspended solids (TSS), nitrates (NO₃), phosphates (PO₄), temperature, turbidity, and pH. McClelland’s index then converts the concentrations of these water quality measures (milligrams per liter) into a corresponding score on a continuous scale ranging between 0 and 100. These scores were calculated by averaging the judgments from 142 water quality experts regarding the functional relationship between the conventional concentration measures and a 0-100 scale. Weights for each of the nine water quality characteristics were designed to sum to one and were again based on the judgments of the water

1More information regarding the SPARROW model can be found at the following web address http://water.usgs.gov/nawqa/sparrow/
quality experts. The measures scores and weights were combined in a multiplicative index of the following form:

\[ \prod_{i=1}^{n} q_i^{w_i} \]  

(2.1)

where \( q_i \) = water quality score ranging between 0 and 100
\( w_i \) = weight for each of the \( i \) water quality parameters; \( i = 1, 2, \ldots, n \)

Temperature, turbidity, and pH however are not modeled in NWPCAM and the index originally created by McClelland had to be modified to account for their omission. The new WQI now contains six water quality parameters (\( n = 6 \) in equation 2.1) and translates NWPCAM results into a continuous WQI with values ranging between 0 and 100. New weights were calculated so that the ratios of the six remaining weights were retained and would still sum to one.

### 2.3 MODEL PROCESS AND TECHNICAL APPROACH FOR EVALUATING GHG POLICY SCENARIOS

To link GHG mitigation actions in agriculture and forestry to changes in water quality, we integrated changes in the ASMGHG environmental accounts for nitrogen (N), phosphorous (P), and erosion-total suspended solids (TSS) under alternative GHG prices into the input used by NWPCAM. In turn, NWPCAM was used to estimate changes in the incidence of nitrogen (N), phosphorous (P), and total suspended solids (TSS) in the nation’s waters along with estimates of changes in water quality. We compared “baseline” conditions (circa late 1990s) with two scenarios (circa 2020), which reflect agricultural and forestry reactions to two different prices for GHG ($25 and $50 per tonne of C equivalent), as reflected in ASMGHG outputs (e.g., land use and agricultural practices). These hypothetical carbon prices were selected to represent values in the mid-range of prices typically evaluated for land-based carbon mitigation and not to find the optimal carbon price to reach a desired level of water quality improvement. Rather, this research is aimed at estimating the environmental benefits additional to the GHG emission reductions. An overview of the model system is presented in Figure 2-1.

ASMGHG chooses regional crop mix, tillage practices, fertilizer use and land allocation between crop, grazing, and forest uses based on relative economic returns, inclusive of returns to GHG fluxes. Thus,
it provides GHG scenario level data on changes in land-use, crop acreage and livestock holdings for the 63 regions in the model.\textsuperscript{2}

While this is a fairly fine level of spatial detail for economic analysis, it is not sufficiently detailed for water quality modeling. Thus, additional spatial mapping was required to incorporate the results into NWPCAM.

For N, P, and TSS loadings from cropland, ASMGHG results were further broken down to the county level using an auxiliary multiple objective programming model (Atwood et al 2000) which allocates the ASMGHG 63 region level crop mix changes to counties in a fashion most consistent with the USDA’s Natural Resource Inventory (NRI) and Agricultural Census observations on observed county level cropping patterns. This allows the loadings calculated to be mapped by county-FIPS code to the 1 km\textsuperscript{2} grid cells in NWPCAM.

\textsuperscript{2}Note, we do not factor in other sectors of the economy or non-US agricultural markets experiencing a C prices.
Because ASMGHG and NWPCAM use different land use categorizations, we had to build a cross-link to ensure that land use categories used in ASMGHG are reasonably mapped to the land use/cover categories used in NWPCAM. The percentage change in loadings of the selected pollutants calculated in ASMGHG are processed in NWPCAM using data-intensive procedures that account for NWPCAM’s need to take every 1 km² grid cell loading, transport it to the nearest RF3 Reach, and then transport and decay the combined loadings (including, for instance point sources) down the river network.

The percentage change in loadings calculated in ASMGHG due to changes in the alternative GHG prices are used to influence the export coefficients created in NWPCAM. We use percentage changes in loadings instead of absolute changes because ASMGHG and NWPCAM use different methods for estimating loadings. It would be difficult to resolve (calibrate) these differences on an absolute basis and then arrive at the “truth.” Estimating nonpoint source (NPS) loadings is complex and the export coefficient methodology used in NWPCAM is a highly scale-dependent modeling approach. For instance, export from a 1-hectare field is very different from export from a 100-hectare watershed. The export coefficients represent not only field-scale processes but also transport and decay processes at the scale being modeled. Resolving scale differences between ASMGHG and NWPCAM is beyond the scope of this study. Additionally, although NWPCAM models water quality changes occurring from the loadings on individual land use cells at the RF3 reach level, the percentage change in pollutant levels enter or “shock” the model at the RF1 level. Because the RF3 network is a sub-set of the more generalized RF1 network, in stream decay kinetics are used to model loading by land use through the RF3 system to the RF1 reach level and then altered by the percentage change in loadings. These changes in loadings are then modeled through the full RF1 system in NWPCAM producing the water quality changes presented in Section 3.

The process of incorporating ASMGHG into NWPCAM accomplishes several things. The changes in loadings will occur in

---

3We were unable to map 5 of the approximately 3000 counties because of imperfect overlap of the two model databases, reflecting somewhat incomplete coverage.
NWPCAM in a spatial pattern that reflects land use within the given county. For instance, if the southeast portion of the county contains most of the agricultural land while the northeast portion is forested, then most of the loadings changes will take place in the southeast. These loading changes will then be routed to the river reaches that correspond to the areas where the predominant land use is agricultural. Therefore, the reaches in the southeast portion of the county will experience the greatest changes as influenced by the changes implied by ASMGHG. The watershed boundaries defined by the RF3 and RF1 reaches used in NWPCAM may in many instances divide the county into several regions. Using this spatial assignment of land use and pollutant loadings, more precise levels of loadings are directed to the appropriate RF3 and thus RF1 reaches. The northern portion of the county may be in one watershed and the southern portion in another watershed, and the major loading changes will thus properly wind up in the southern watershed. This allows more accurate water quality estimates than simply assigning a level of loadings to the county as one large unit and one watershed or set of river reaches.

It is beyond the scope of this report to provide further details concerning the full modeling processes and in-stream kinetics used in NWPCAM. More detail about NWPCAM (including an application) can be found online at:
http://www.epa.gov/waterscience/economics/
http://www.epa.gov/ost/guide/cafo/economics.html#envir

However, Figure 2-2 presents a detailed overview of the NWPCAM-ASMGHG processes used in this study. There are seven major steps and associated sub-steps in this integration process. These actions are numbered in Figure 2-2 with the following notation, n.m, where n is a major step (1-7), and m is a sub-step within a given step. For example, “3.3” involves the major step modeling nonpoint source (NPS) loadings (3.m) and the sub-step routing these loadings to the RF3 reaches (n.3).

The overall procedure is to connect the various loadings categories to the finer-scale RF3 Reaches, then model these loadings down the RF3 network to the coarser-scale Reach File Version 1 (RF1). This is possible because of a cross-link in the RF3 and RF1 reach systems. The actual in-stream modeling of baseline and GHG pricing scenarios is performed using an enhanced version of NWPCAM at
Figure 2-2. The NWPCAM Modeling System for Water Quality Co-Benefits Due to GHG Mitigation Policies in LUCF
the RF1 reach level. RF1 is used for the modeling and presentation results for two reasons. The information in the modeling system at the RF3 reach level has a higher degree of error than at the RF1 reach level; the NWPCAM processes tend to even out the data variability as the modeling works its way downstream to the larger rivers and streams as represented in RF1. In addition, the RF3 network is much too dense to be able to meaningfully map the results at a national scale.

Below is a brief discussion on the modeling processes in NWPCAM and the crosswalk between ASMGHG and NWPCAM illustrated in Figure 2-2. Because the two models are completely separable and stand alone Steps 1-5 (NWPCAM processes) and Step 5 (ASMGHG processes) can be run simultaneously or separately and in any order (ASMGHG processes or NWPCAM processes first). It is not until Step 6 where the two models are combined by incorporating ASMGHG results into NWPCAM, that the models are coordinated.

**Step 1.** This step in the NWPCAM modeling process involves the transfer of animal manure loadings from county-level estimates of Animal Feeding Operations (AFOs) to individual agricultural land cover cells. The manure loadings database accounts for onsite and offsite loadings from all operations with greater than 300 animal units. The source loadings databases take existing regulations into account. In addition, effluent guideline scenarios are available for modeling as well. Once assigned to the land cover cells, the loadings are routed/decayed to the full RF3 network. From there, the loadings are routed/decayed to RF1 reaches before being integrated into the NWPCAM Version 1.6 system in Step 6. Note, animal loadings are developed for baseline water quality estimates only and, as yet, not for changes in these loadings in response to GHG pricing.4

**Step 2.** This step transfers municipal, industrial, and combined sewer overflow loadings from the RF3 to the RF1 reaches. This transfer is conducted through decay kinetics applied along the RF3

---

4A more complete analysis of carbon sequestration pricing of water quality changes can be performed by modifying Step 1. The animal manure loadings could be tracked by reach and county in a process analogous to the processing performed in Step 4. The manure loadings could even be modified according to facility type, such as beef, veal, poultry, etc. Scenario modeling would then be done by simultaneously operating on the nonmanure NPS loadings represented in Step 4 and the manure-related NPS loadings from Step 1.
reaches until the loadings reach RF1. These loadings also enter the NWPCAM system in Step 6.

**Step 3.** Here the nonagricultural, nonpoint source (NPS) loadings from a loadings database are transferred to land cover cells and RF1 and RF3 reaches using a process similar to that used for Step 1. These nonagricultural loadings by RF1 reach are the utilized in NWPCAM in Step 6.

**Step 4.** This step is a departure from the previous NWPCAM processes and was developed especially for this project. The nonmanure-related, agricultural NPS loadings from Step 3.1 are split out from the master NPS database and routed/decayed for each land cover cell, keeping track of loadings on a reach-county basis. This detailed tracking provides a database of RF1-level agricultural loadings (nonmanure) on an RF1-county basis that is used to simulate loadings changes due to GHG pricing scenarios.

**Step 5.** This step converts changes in ASMGHG county-level loadings of TSS, N, and P to percent changes from the baseline for each policy scenario.\(^5\)

**Step 6.** This is where all of the loadings estimates, the RF1 reaches, and the ASMGHG percent changes are combined for the NWPCAM model runs. The NWPCAM agricultural loadings changes are assumed to be linear functions of the ASMGHG-derived percentage change loadings by county. This is a reasonable assumption because the modeling of decay kinetics from the individual land cover cells to RF1 reaches is all linear. In Step 6, the baseline (no changes in agricultural NPS loadings) and alternative GHG pricing scenarios are modeled.

**Step 7.** This final step involves processing the results of each model run. The results are summarized in the tables presented in Section 3 of this report. Data summaries by RF1 reach are merged into a GIS coverage creating a national water quality map (for example, Figure 3-1).

Figure 2.2 identifies Step 5 as ASMGHG processes conducted before being integrated into NWPCAM. There are four major steps

---

\(^5\)Because this discussion is focused on the NWPCAM integration process a more detailed description of the processes and integration of ASMGHG results will follow the discussion of Figure 2.2
or processes that are involved in moving from Step 5.1 to Step 5.5 and finally integrating results with NWPCAM in Step 6.2. These four steps include:

1. Developing baseline agricultural and forestry sector conditions,
2. Generating conditions under the two alternative pricing scenarios,
3. Allocating land use and loadings to county levels, and
4. Computing percentage changes in loadings measures and integrate with NWPCAM.

A detailed discussion of the processes of ASMGHG can be found in McCarl and Schneider (2000) and Chang et al. (1992).
Model Results

This section presents outputs from integrating ASMGHG and NWPCAM at three levels: national, regional and case-studies. The national results provide a broad representation of the potential impacts the GHG pricing alternatives will have on the agricultural and forestry sectors, GHG mitigation, environmental pollutants, and water quality. The regional impacts give us a geographic breakdown of the overall results. Finally, two case studies allow us to put a magnifying glass on the “hot spots” where the potential benefits from both GHG mitigation and improved water quality are substantial.

3.1 NATIONAL-LEVEL RESULTS

The “baseline” conditions circa late 1990s (no GHG price) are estimated and then compared to two scenarios circa 2020. These two scenarios reflect the different prices for sequestered or released GHG’s ($25 and $50 per tonne of C equivalent). The introduction of these price incentives causes ASMGHG to change its equilibrium allocation of land use, tillage, fertilization, crop mix and other management practices, commodity production and consumption, trade flows, and environmental loadings. The environmental loadings are then transferred into NWPCAM to model the resulting changes in water quality.

3.1.1 Economic Welfare Impacts

The national level results generated by ASMGHG are presented in Table 3-1. Impacts of the two GHG prices are described in terms of three major categories: (1) economic welfare, (2) greenhouse gases, (3) environmental variables and land/use land cover. The list of bulleted items below highlights the key national economic results generated by the GHG incentive payments. Results common to both GHG prices are:
Table 3-1. National Summary of Welfare, Agricultural, and Environmental Impacts under Three GHG Prices

<table>
<thead>
<tr>
<th></th>
<th>Unit</th>
<th>Baseline $0/Tonne of CE</th>
<th>$25/Tonne of CE</th>
<th>$50/Tonne of CE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Welfare:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>U.S. producer welfare</td>
<td>billion $</td>
<td>30.93</td>
<td>31.84</td>
<td>36.73</td>
</tr>
<tr>
<td>U.S. consumer welfare</td>
<td>billion $</td>
<td>1183.15</td>
<td>1181.49</td>
<td>1177.50</td>
</tr>
<tr>
<td>Rest of the world welfare</td>
<td>billion $</td>
<td>256.64</td>
<td>256.15</td>
<td>255.37</td>
</tr>
<tr>
<td>Total social welfare (TSW)</td>
<td>billion $</td>
<td>1470.72</td>
<td>1469.48</td>
<td>1469.59</td>
</tr>
<tr>
<td>TSW less GHG payments</td>
<td>billion $</td>
<td>1470.72</td>
<td>1469.86</td>
<td>1467.00</td>
</tr>
<tr>
<td><strong>Agricultural Activities:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop production index</td>
<td>Base = 100</td>
<td>100.0</td>
<td>98.16</td>
<td>95.68</td>
</tr>
<tr>
<td>All goods production index (includes biofuels)</td>
<td>Base = 100</td>
<td>100.0</td>
<td>99.05</td>
<td>97.66</td>
</tr>
<tr>
<td>Crop price index</td>
<td>Base = 100</td>
<td>100.0</td>
<td>102.65</td>
<td>108.42</td>
</tr>
<tr>
<td>All goods price index</td>
<td>Base = 100</td>
<td>100.0</td>
<td>101.63</td>
<td>106.32</td>
</tr>
<tr>
<td>U.S. export sales</td>
<td>billion $</td>
<td>16.00</td>
<td>15.48</td>
<td>15.14</td>
</tr>
<tr>
<td><strong>Land Use:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dry land</td>
<td>$10^6$ acres</td>
<td>240.78</td>
<td>240.65</td>
<td>227.01</td>
</tr>
<tr>
<td>Irrigated land</td>
<td>$10^6$ acres</td>
<td>60.21</td>
<td>56.18</td>
<td>58.15</td>
</tr>
<tr>
<td>Pasture land</td>
<td>$10^6$ acres</td>
<td>395.16</td>
<td>396.01</td>
<td>390.95</td>
</tr>
<tr>
<td>Afforestation</td>
<td>$10^6$ acres</td>
<td>0.000</td>
<td>5.80</td>
<td>12.52</td>
</tr>
<tr>
<td>Irrigation water use</td>
<td>$10^6$ acre-feet</td>
<td>73.08</td>
<td>67.39</td>
<td>68.20</td>
</tr>
<tr>
<td><strong>Environment:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nitrogen</td>
<td>$10^6$ tons</td>
<td>7.88</td>
<td>7.64</td>
<td>7.41</td>
</tr>
<tr>
<td>Phosphorus</td>
<td>$10^6$ tons</td>
<td>1.65</td>
<td>1.62</td>
<td>1.57</td>
</tr>
<tr>
<td>Potassium</td>
<td>$10^6$ tons</td>
<td>2.41</td>
<td>2.41</td>
<td>2.39</td>
</tr>
<tr>
<td>Pesticide</td>
<td>$10^6$ dollars</td>
<td>7279.66</td>
<td>7345.05</td>
<td>6990.86</td>
</tr>
<tr>
<td>Erosion (TSS)</td>
<td>$10^6$ tons</td>
<td>3525.63</td>
<td>3541.66</td>
<td>3272.82</td>
</tr>
<tr>
<td><strong>Greenhouse Gas:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CH$_4$</td>
<td>MMTCE</td>
<td>46.28</td>
<td>45.27</td>
<td>41.43</td>
</tr>
<tr>
<td>CO$_2$</td>
<td>MMTCE</td>
<td>29.53</td>
<td>-57.48</td>
<td>-119.75</td>
</tr>
<tr>
<td>N$_2$O</td>
<td>MMTCE</td>
<td>28.40</td>
<td>27.14</td>
<td>26.22</td>
</tr>
<tr>
<td>Total</td>
<td>MMTCE</td>
<td>104.20</td>
<td>14.93</td>
<td>-52.10</td>
</tr>
</tbody>
</table>
Decline in agricultural production (traditional crop production offset partially by bio-fuel production and limited afforestation)

Rise in agricultural prices

Losses in consumer welfare due to higher prices

Gains in producer welfare due to higher food prices and market or government payments for the new commodity GHG offsets

Losses in exports earnings.

Agricultural producers gain just over $900 million and $5.8 billion respectively under the low and high GHG price scenarios. Taking into account consumer losses, the total welfare costs of the incentive system would be about $1.1–1.2 billion. These costs need to be balanced against welfare gains in other parts of the economy in terms of reduced GHG damages, reduced mitigation costs in the nonagricultural sectors, and co-benefits. Those welfare gains are not estimated in this study.

3.1.2 GHG Mitigation from all Modeled Activities

Table 3-1 also shows total changes in net GHG emission resulting from the carbon pricing scenarios and agricultural practices. Within ASMGHG, greenhouse gas emissions and emission reductions are accounted for all major sources, sinks and offsets from agricultural activities and for which data were available or could be generated. As we will explain below, some of the GHG mitigation reported in Table 3-1 comes from activities for which corresponding water quality effects could not be estimated with the current modeling system. However, it is instructive to begin the discussion with this broader estimate of GHG mitigation from agriculture and forestry.

National GHG emissions decline from about 104.2 million metric tonnes of carbon equivalent (MMTCE) per year in the baseline to 14.9 MMTCE per year under the lower carbon pricing scenario (a GHG reduction benefit of 89.3 MMTCE/yr). At the high GHG price, agriculture becomes a net sink of –52.1 MMTCE/year (GHG mitigation of 156.3 MMTCE/year). All species of GHG are reduced by the incentive responses, but the effects are most dramatic for CO₂ with low- or no-tillage crop management occurring at the low price and the biofuel offsets kicking in at the higher price.
3.1.3 Agricultural Mitigation and Environmental Loadings

The mitigation actions and environmental impacts resulting from the two GHG pricing scenarios are also presented in Table 3-1. The results suggest a drop in the amount of traditionally cropped agricultural land under both GHG prices. The acres of irrigated lands also decline as the price of GHG is increased. Finally, because forest is a more carbon-intensive land use than agriculture, the amount of agricultural land afforested increases with the price incentives (baseline equals zero, all values represent lands being afforested).

Impacts associated with these changes in land use/land cover (LULC) are changes in the loadings of nitrogen (N), phosphorous (P), potassium (K), pesticides, and erosion or total suspended solids (TSS). The ASMGHG results show a decline in loadings for nitrogen and phosphorous at the low price scenario, and a reduction in all loadings at the higher GHG price. The most dramatic reduction in loadings is in TSS at the higher GHG price. Results reveal a potential reduction in TSS loading of over 252 million tons.

3.1.4 National Water Quality Results

As described in Section 2.3, NWPCAM considers changes in N, P, and TSS as a representation of the most prominent nutrients and conventional pollutants likely to change as a result of land use changes and impact water quality conditions. Reductions in the loading of these pollutants will cause the localized WQI to increase. Recollect, ASMGHG reports county-level nutrient results for cropland only. As a result, the impacts on water quality focus entirely on cropland. Although livestock manure loadings and afforestation are reported for the 63 ASMGHG regions, the data from "large" ASMGHG regions are too coarse for the finer scale resolution of NWPCAM.\(^1\) As a result, this analysis provides a partial, but important, picture of water quality effects.

Table 3-2 presents the changes in water quality at the national level and also at the disaggregated regional level. These WQI values are weighted averages of reach-specific values, with the stream mile per reach constituting the weights. That is, the WQI values in Table 3-2

\(^1\)We plan to model the effects of manure loadings and forest loadings in future work.
Table 3-2. Regional Water Quality Indices (WQI) Under the Baseline and Alternative GHG Pricing Scenarios

<table>
<thead>
<tr>
<th>ASMGHG Region</th>
<th>Total Length of Reach System (Mi.)</th>
<th>Baseline WQI</th>
<th>Change in WQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>45,082.80</td>
<td>74.16</td>
<td>0.12</td>
</tr>
<tr>
<td>Lake States</td>
<td>39,994.20</td>
<td>65.16</td>
<td>2.64</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>64,636.20</td>
<td>57.64</td>
<td>2.57</td>
</tr>
<tr>
<td>North Plains</td>
<td>63,724.30</td>
<td>50.29</td>
<td>3.96</td>
</tr>
<tr>
<td>Appalachia</td>
<td>59,892.10</td>
<td>79.53</td>
<td>0.20</td>
</tr>
<tr>
<td>Southeast</td>
<td>45,107.50</td>
<td>80.90</td>
<td>0.57</td>
</tr>
<tr>
<td>Delta States</td>
<td>35,070.70</td>
<td>78.77</td>
<td>2.34</td>
</tr>
<tr>
<td>South Plains</td>
<td>62,293.30</td>
<td>55.39</td>
<td>2.96</td>
</tr>
<tr>
<td>Mountain</td>
<td>173,854.00</td>
<td>69.37</td>
<td>0.36</td>
</tr>
<tr>
<td>Pacific</td>
<td>73,426.50</td>
<td>76.59</td>
<td>0.25</td>
</tr>
<tr>
<td>Total U.S.</td>
<td>632,532.00</td>
<td>68.56</td>
<td>1.38</td>
</tr>
</tbody>
</table>

Note 1: Total length of miles of the ASMGHG regions is greater than the total miles because some reaches are in more than one region.
Note 2: Delta WQI values are scenario weighted sums minus baseline weighted sums, so positive values indicate water quality improvements.

are aggregated weighted averages and are not intended to suggest that all waters in the US or one of the sub-regions have the WQI reported.

In the context of the Clean Water Act of 1972, a WQI between 25 and 49 represents boatable waters, between 50 and 69 correspond to fishable waters, and between 70 and 94 are swimmable.\(^2\) From Table 3-2 we can see that the aggregate baseline water quality for the entire U.S. falls in the upper range of fishable, nearly reaching swimmable levels. This is, in some sense, a measure of average

\(^2\)The passage of the Federal Water Pollution Control Act of 1972 (FWPCA-72) established national water quality objectives and identified a number of goals in order to ensure the achievement of these objectives. Later amendments to the FWPCA-72 lead to the passage of the Clean Water Act of 1977 (CWA). Section 1251 of the Clean Water Act defines the goal of establishing “boatable and fishable” water quality conditions in the nation’s waters by 1985. However, in the 1998 National Water Quality Inventory Report to Congress, it was reported that about 40 percent of the streams that were monitored by the EPA were not clean enough to be classified as fishable or swimmable.
water quality nationwide. The reductions in loadings that result from the GHG mitigation activities increase the national aggregate average water quality 1.38 points (about 2 percent) on a 1 to 100 scale. These improvements move the aggregate water quality measure into the swimmable range.

The maps presented in Figures 3-1 and 3-2 (corresponding to the $25 and $50 scenarios respectively) visually summarizes the information presented in Table 3-2. The unit of change presented in the maps is the change in the WQI from the baseline conditions. The reductions in water quality (–40 to –1) represents the bottom 5 percent of all reaches in the country. The remaining reaches are broken down into three additional categories; no change (0), a positive improvement (1–5), and the top 5 percent of reach-level improvement in the country.³

Figure 3-1. Changes in Water Quality Indices (WQI) by Reach: $25/Tonne Scenario Compared to Baseline

Note: Positive values represent improved water quality.

³This same unit of change is used for all maps presented in this report. The categories are reaches: (a) showing some impairment (the bottom 5 percent), (b) experiencing no change, (c) showing some improvement, and (d) showing the greatest improvements (top 5 percent) as a result of the GHG incentives.
An interesting result reveals that regardless of the price of GHG, the improvement in water quality on the national scale will be the same magnitude. This offers some evidence of diminishing returns to water quality—that is, additional ASMGHG loadings are small in comparison to other loadings into the hydrologic system to cause system wide water quality effects. We will return to this issue in the discussion section (Section 4). Moreover, regional differences in WQI changes can also explain this result to some extent. Some regions show a larger improvement in water quality under the smaller GHG price than the higher price, while the opposite is true in other regions. In order to gain a better understanding of what is actually happening to the water quality, a more fine scale analysis and detailed discussion is presented in the regional results section below.
3.2 REGIONAL RESULTS

Because national level aggregation masks the results that occur at the local level, we look at some regional breakouts in this section. This regional assessment feeds our development and discussion of the Case Studies in Section 3.3. The regional results for the farmland impacts of GHG pricing are aggregated from the original 63 ASMGHG regions into 10 broader regions presented in Table 3-3. We use these definitions to disaggregate our results.

Table 3-3. Regional Definitions

<table>
<thead>
<tr>
<th>ASMGHG Region</th>
<th>States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont</td>
</tr>
<tr>
<td>Lake States</td>
<td>Michigan, Minnesota, Wisconsin</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>Illinois, Indiana, Iowa, Missouri, Ohio</td>
</tr>
<tr>
<td>North Plains</td>
<td>Kansas, Nebraska, North Dakota, South Dakota</td>
</tr>
<tr>
<td>Appalachia</td>
<td>Kentucky, North Carolina, Tennessee, Virginia, West Virginia</td>
</tr>
<tr>
<td>Southeast</td>
<td>Alabama, Florida, Georgia, South Carolina</td>
</tr>
<tr>
<td>Delta States</td>
<td>Arkansas, Louisiana, Mississippi</td>
</tr>
<tr>
<td>South Plains</td>
<td>Oklahoma, Texas</td>
</tr>
<tr>
<td>Mountain</td>
<td>Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming</td>
</tr>
<tr>
<td>Pacific</td>
<td>California, Oregon, Washington</td>
</tr>
</tbody>
</table>

3.2.1 GHG Mitigation from Cropland Activities

Table 3-4 presents GHG mitigation on cropland by each region under baseline and the two GHG incentive prices ($25 and $50). It is important to note that the GHG mitigation estimates in Table 3-4 are only for the changes in cropland practices associated the water quality changes modeled here. Therefore the national total in Table 3-4 is a subset of the national total in Table 3-1, because Table 3-1 includes the GHG mitigation from afforestation and livestock practices for which we were not able to estimate water quality impacts. This ensures that we are comparing GHG mitigation and water quality effects for the same set of activities.
Table 3-4. GHG (Sum of CO₂, CH₄, and N₂O) Results from Cropland by Census Region in MMTCE

<table>
<thead>
<tr>
<th>Region</th>
<th>Million Acres</th>
<th>Base</th>
<th>Actual Value</th>
<th></th>
<th>Absolute Change</th>
<th></th>
<th>Percentage Change</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$25/Tonne of CE</td>
<td>$50/Tonne of CE</td>
<td>$25/Tonne of CE</td>
<td>$50/Tonne of CE</td>
<td>$25/Tonne of CE</td>
<td>$50/Tonne of CE</td>
</tr>
<tr>
<td>Northeast</td>
<td>11.09</td>
<td>1.61</td>
<td>0.40</td>
<td>0.26</td>
<td>−1.21</td>
<td>−1.35</td>
<td>−74.95</td>
<td>−83.74</td>
</tr>
<tr>
<td>Lake States</td>
<td>34.92</td>
<td>3.41</td>
<td>−4.88</td>
<td>−6.14</td>
<td>−8.29</td>
<td>−9.55</td>
<td>−242.96</td>
<td>−280.04</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>85.50</td>
<td>16.47</td>
<td>−10.73</td>
<td>−12.70</td>
<td>−27.20</td>
<td>−29.17</td>
<td>−165.13</td>
<td>−177.13</td>
</tr>
<tr>
<td>North Plains</td>
<td>66.86</td>
<td>4.36</td>
<td>−6.74</td>
<td>−7.13</td>
<td>−11.10</td>
<td>−11.49</td>
<td>−254.54</td>
<td>−263.54</td>
</tr>
<tr>
<td>Appalachia</td>
<td>14.39</td>
<td>2.50</td>
<td>0.68</td>
<td>0.74</td>
<td>−1.82</td>
<td>−1.77</td>
<td>−72.85</td>
<td>−70.60</td>
</tr>
<tr>
<td>Southeast</td>
<td>9.44</td>
<td>0.67</td>
<td>−0.08</td>
<td>−0.16</td>
<td>−0.75</td>
<td>−0.83</td>
<td>−111.83</td>
<td>−124.24</td>
</tr>
<tr>
<td>Delta States</td>
<td>18.06</td>
<td>4.38</td>
<td>2.94</td>
<td>1.99</td>
<td>−1.44</td>
<td>−2.39</td>
<td>−32.79</td>
<td>−54.54</td>
</tr>
<tr>
<td>South Plains</td>
<td>28.03</td>
<td>4.48</td>
<td>−1.79</td>
<td>−1.62</td>
<td>−6.26</td>
<td>−6.10</td>
<td>−139.92</td>
<td>−136.24</td>
</tr>
<tr>
<td>Mountain</td>
<td>21.68</td>
<td>4.52</td>
<td>1.97</td>
<td>1.77</td>
<td>−2.55</td>
<td>−2.74</td>
<td>−56.47</td>
<td>−60.75</td>
</tr>
<tr>
<td>Pacific</td>
<td>11.03</td>
<td>4.88</td>
<td>2.60</td>
<td>2.41</td>
<td>−2.28</td>
<td>−2.47</td>
<td>−46.68</td>
<td>−50.59</td>
</tr>
<tr>
<td>Total U.S.</td>
<td>301.00</td>
<td>47.28</td>
<td>−15.62</td>
<td>−20.59</td>
<td>−62.90</td>
<td>−67.87</td>
<td>−133.03</td>
<td>−143.55</td>
</tr>
</tbody>
</table>

In Table 3-4, GHGs are summed across three component species (CO₂, CH₄, and N₂O). As indicated in Table 3-1, CO₂ is the dominant GHG factor in agriculture. Positive values of GHG indicate net emissions, negative values indicate net sequestration. Each of the 10 regions show a decline in GHG emissions, half of them becoming carbon sinks (negative net emissions). The region with the largest change at both GHG prices is the Corn Belt. Croplands in this region account for a net reduction of 27.2 MMTCE/year at the $25/tonne price and 29.2 MMTCE/year at the higher price of $50/tonne. For most regions, GHG mitigation is not substantially higher at $50 than at $25, thereby implying diminishing returns to the cropland mitigation activities. In essence, much of the GHG gains from cropland activities through tillage changes are realized at the lower price. Incremental opportunities are harder to realize.

### 3.2.2 Pollutant Loadings

Table 3-5 presents N, P, and TSS cropland loadings. There are two discernible patterns in these results. First, the largest change in loadings is for TSS where there is considerable regional
### Table 3-5. N, P, and TSS Loadings (Million Tons) from Cropland by Region

<table>
<thead>
<tr>
<th>Region</th>
<th>Million Acres</th>
<th>Base</th>
<th>Actual Value</th>
<th>Absolute Change</th>
<th>Percentage Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$25/Tonne CE</td>
<td>$50/Tonne CE</td>
<td>$25/Tonne CE</td>
</tr>
<tr>
<td><strong>TSS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>11.09</td>
<td>176.05</td>
<td>177.06</td>
<td>145.82</td>
<td>1.02</td>
</tr>
<tr>
<td>Lake States</td>
<td>34.92</td>
<td>538.92</td>
<td>537.31</td>
<td>504.89</td>
<td>−1.60</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>85.50</td>
<td>1073.47</td>
<td>1047.32</td>
<td>1053.20</td>
<td>−26.16</td>
</tr>
<tr>
<td>North Plains</td>
<td>66.86</td>
<td>420.33</td>
<td>420.83</td>
<td>407.70</td>
<td>0.50</td>
</tr>
<tr>
<td>Appalachia</td>
<td>14.39</td>
<td>201.07</td>
<td>183.73</td>
<td>214.14</td>
<td>−17.34</td>
</tr>
<tr>
<td>Southeast</td>
<td>9.44</td>
<td>106.78</td>
<td>106.98</td>
<td>62.19</td>
<td>0.21</td>
</tr>
<tr>
<td>Delta States</td>
<td>18.06</td>
<td>591.15</td>
<td>638.28</td>
<td>471.27</td>
<td>47.13</td>
</tr>
<tr>
<td>South Plains</td>
<td>28.03</td>
<td>277.63</td>
<td>266.40</td>
<td>244.74</td>
<td>−11.23</td>
</tr>
<tr>
<td>Mountain</td>
<td>21.68</td>
<td>85.37</td>
<td>83.40</td>
<td>82.38</td>
<td>−1.97</td>
</tr>
<tr>
<td>Pacific</td>
<td>11.03</td>
<td>54.86</td>
<td>80.34</td>
<td>86.48</td>
<td>25.48</td>
</tr>
<tr>
<td><strong>Total U.S.</strong></td>
<td>301.00</td>
<td>3,525.63</td>
<td>3,541.66</td>
<td>3,272.82</td>
<td>16.03</td>
</tr>
<tr>
<td><strong>Nitrogen</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>11.09</td>
<td>0.52</td>
<td>0.51</td>
<td>0.40</td>
<td>−0.01</td>
</tr>
<tr>
<td>Lake States</td>
<td>34.92</td>
<td>0.76</td>
<td>0.76</td>
<td>0.72</td>
<td>−0.01</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>85.50</td>
<td>2.48</td>
<td>2.42</td>
<td>2.44</td>
<td>−0.06</td>
</tr>
<tr>
<td>North Plains</td>
<td>66.86</td>
<td>0.78</td>
<td>0.78</td>
<td>0.85</td>
<td>0.00</td>
</tr>
<tr>
<td>Appalachia</td>
<td>14.39</td>
<td>0.63</td>
<td>0.63</td>
<td>0.74</td>
<td>0.00</td>
</tr>
<tr>
<td>Southeast</td>
<td>9.44</td>
<td>0.28</td>
<td>0.29</td>
<td>0.22</td>
<td>0.00</td>
</tr>
<tr>
<td>Delta States</td>
<td>18.06</td>
<td>0.52</td>
<td>0.49</td>
<td>0.39</td>
<td>−0.02</td>
</tr>
<tr>
<td>South Plains</td>
<td>28.03</td>
<td>0.66</td>
<td>0.60</td>
<td>0.55</td>
<td>−0.05</td>
</tr>
<tr>
<td>Mountain</td>
<td>21.68</td>
<td>0.96</td>
<td>0.87</td>
<td>0.82</td>
<td>−0.08</td>
</tr>
<tr>
<td>Pacific</td>
<td>11.03</td>
<td>0.29</td>
<td>0.27</td>
<td>0.27</td>
<td>−0.02</td>
</tr>
<tr>
<td><strong>Total U.S.</strong></td>
<td>301.00</td>
<td>7.88</td>
<td>7.64</td>
<td>7.41</td>
<td>−0.24</td>
</tr>
<tr>
<td><strong>Phosphorus</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>11.09</td>
<td>0.08</td>
<td>0.08</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Lake States</td>
<td>34.92</td>
<td>0.22</td>
<td>0.22</td>
<td>0.21</td>
<td>0.00</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>85.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.00</td>
</tr>
<tr>
<td>North Plains</td>
<td>66.86</td>
<td>0.23</td>
<td>0.24</td>
<td>0.24</td>
<td>0.00</td>
</tr>
<tr>
<td>Appalachia</td>
<td>14.39</td>
<td>0.09</td>
<td>0.09</td>
<td>0.11</td>
<td>0.00</td>
</tr>
<tr>
<td>Southeast</td>
<td>9.44</td>
<td>0.06</td>
<td>0.06</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td>Delta States</td>
<td>18.06</td>
<td>0.10</td>
<td>0.10</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>South Plains</td>
<td>28.03</td>
<td>0.14</td>
<td>0.12</td>
<td>0.11</td>
<td>−0.02</td>
</tr>
<tr>
<td>Mountain</td>
<td>21.68</td>
<td>0.13</td>
<td>0.12</td>
<td>0.12</td>
<td>−0.01</td>
</tr>
<tr>
<td>Pacific</td>
<td>11.03</td>
<td>0.10</td>
<td>0.09</td>
<td>0.09</td>
<td>−0.01</td>
</tr>
<tr>
<td><strong>Total U.S.</strong></td>
<td>301.00</td>
<td>1.65</td>
<td>1.62</td>
<td>1.57</td>
<td>−0.03</td>
</tr>
</tbody>
</table>
heterogeneity among the level of loadings. In addition to the loading differences among regions, there is also some significant heterogeneity for TSS at the two GHG prices. For example, the Southeast, Northeast, and North Plains regions generate larger loadings of TSS at the low price, but substantially reduce loadings at the higher price. However, the opposite pattern is implied in the Appalachian region. These stark inter-regional differences are not found in N and P. The divergent patterns reflect the complex relationship between GHG incentives, changes in practices, crop mix and aggregate pollutant loadings.

Second, while there is evidence of regional heterogeneity in the changes in N and P loadings associated with GHG mitigation, the overall changes are relatively small. All of the regions show a small reduction or no change in the loadings of these pollutants from the baseline conditions at the low price. The heterogeneity is more easily identified at the higher price where some of the regions that initially had no change in the baseline loadings now show a slight reduction and, in some cases, an increase. For example, the Southeast and North Plains regions show no change from the baseline loadings of nitrogen at the low price. However, the higher GHG price reveals that the Southeast exhibits a reduction in nitrogen loadings while the North Plains shows an increase. Again, these are relatively small changes from the baseline conditions.

### 3.2.3 Regional Water Quality Results

Table 3-2 shows the weighted regional water quality indexes calculated by NWPCAM. The majority of the improvements are in five of the regions across the U.S., all of which improve by 2.5 points or more. The North Plains region had the lowest baseline WQI and realizes the largest improvement (8 percent) from land use transitions and reductions in loadings as modeled by ASMGHG. The South Plains, Lake States, Corn Belt, and Delta States regional WQI increase by over three percent, rounding out the top 5 regions in water quality improvements. These areas of improved WQI can clearly be seen in Figures 3-1 and 3-2, the national mapping of changes in WQI from the baseline under the two GHG pricing scenarios.

There is an interesting phenomenon that occurs with the WQI under the two GHG prices. All of the regions show an improvement in
water quality under the initial GHG pricing scenario. However, under the higher price scenario, the changes from the baseline conditions are about the same as at the lower GHG price. Although there are still improvements under the higher GHG price, the results reveal that increased GHG mitigation produces increased water quality improvements at a diminishing rate. Recall from Table 3-1 that GHG mitigation on cropland is not substantially higher at the higher price either. Taken together, this is further evidence of positive but diminishing benefits from GHG mitigation efforts on cropland.

### 3.3 CASE STUDIES: BREADBASKET AND GULF STATES

In this subsection, we apply a “magnifying glass” to our analysis. There are at least two ways to dig deep and identify hot-spots. The first definition of a hotspot is in terms of greatest water quality change. A straightforward visual analysis would accomplish this. A second definition of hot-spot, given the “co-effects” nature of this project, is in terms of highest water quality change per unit of GHG mitigated. The latter is accomplished by a numerical analysis relying on the concept of co-benefits elasticity described below. The visual analysis identifies the “Breadbasket” states—Kansas, Nebraska, Iowa, North and South Dakota. The co-benefits elasticity analysis identifies the Gulf States—Texas, Oklahoma, Mississippi, Arkansas, Louisiana. These then comprise our two case studies. Before turning to these, we briefly summarize our approach for measuring co-benefits elasticity.

#### 3.3.1 Co-Benefits Elasticity

The co-benefit elasticity quantifies the synergistic relationship of GHG reductions and improved water quality. Similar to production elasticity, a common measurement in economics, the co-benefit elasticity is calculated using changes in WQI and net GHG emissions. Recall that, from Table 3-4 and the discussion of

---

4In principle, we could also have examined more closely regions for which there are water quality tradeoffs (reductions in quality) with GHG mitigation, but such a result was not found in these scenarios. The outputs produced by the two models in this study differ in magnitude and unit of measurement. In order to compare and evaluate the regions where the synergy between the two benefits is the highest, we developed a comparative measure based on the notion of “elasticity.”
ASMGHG results, percentage changes in GHG emissions from the baseline (no carbon market) were calculated. Using the NWPCAM results under the two pricing scenarios, percentage changes in WQI from the baseline were also calculated. The co-benefit elasticity is calculated using the following equation:

\[
\text{Co-Benefit Elasticity} = \frac{\% \Delta \text{WQI}}{\% \Delta \text{GHG}}
\]

One note on the calculation of this elasticity is that the percentage changes in GHG emissions are based on the absolute value of the change. All GHG results provided by ASMGHG are increased reductions in emissions and, thus, negative values. The changes in WQI, however, are improvements and positive numbers. Therefore, in order to calculate this elasticity, the absolute values are used. A positive co-benefit elasticity indicates positive co-effects from GHG mitigation policies.

A larger co-benefit elasticity represents a higher level of synergy between GHG reductions and water quality improvements in a region. For instance, as changes in WQI increase and levels of GHG reduction remain unchanged or decline, the co-benefit elasticity will increase. Higher elasticity values represent higher level of return in the form of water quality improvements for a given proportional amount of agricultural GHG mitigation.

The co-benefit elasticity measurements presented in Table 3-6 reveal the following pattern. The largest change in water quality with respect to change in GHG emission reduction occurs in the Delta states. This region’s co-benefit elasticity is 0.09 and 0.06 for the two prices, respectively. The higher elasticity measure is the result of the small level of reduction in GHG emissions, resulting in large improvements in water quality. The South Plains, also surrounding the Gulf, present the second largest co-benefit elasticity. This region witnessed large reductions in GHG emissions and large water quality improvements. Collectively these two
### Table 3-6. Co-Benefit Elasticity by Region

<table>
<thead>
<tr>
<th>ASMGHG Region</th>
<th>Percent GHG Change (%)</th>
<th>Percent WQI Change (%)</th>
<th>Co-Benefits Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$25/Tonne of CE</td>
<td>$50/Tonne of CE</td>
<td>$25/Tonne of CE</td>
</tr>
<tr>
<td>Northeast</td>
<td>75 84</td>
<td>0 0</td>
<td>0.00 0.00</td>
</tr>
<tr>
<td>Lake States</td>
<td>243 280</td>
<td>4 4</td>
<td>0.02 0.01</td>
</tr>
<tr>
<td>Corn Belt</td>
<td>165 177</td>
<td>4 4</td>
<td>0.03 0.02</td>
</tr>
<tr>
<td>North Plains</td>
<td>255 264</td>
<td>8 8</td>
<td>0.03 0.03</td>
</tr>
<tr>
<td>Appalachia</td>
<td>73 71</td>
<td>0 0</td>
<td>0.00 0.00</td>
</tr>
<tr>
<td>Southeast</td>
<td>112 124</td>
<td>1 1</td>
<td>0.01 0.01</td>
</tr>
<tr>
<td>Delta States</td>
<td>33 55</td>
<td>3 3</td>
<td>0.09 0.06</td>
</tr>
<tr>
<td>South Plains</td>
<td>140 136</td>
<td>5 6</td>
<td>0.04 0.04</td>
</tr>
<tr>
<td>Mountain</td>
<td>56 61</td>
<td>1 0</td>
<td>0.01 0.01</td>
</tr>
<tr>
<td>Pacific</td>
<td>47 51</td>
<td>0 0</td>
<td>0.01 0.01</td>
</tr>
<tr>
<td>Total U.S.</td>
<td>133 144</td>
<td>2 2</td>
<td>0.02 0.01</td>
</tr>
</tbody>
</table>

Note 1: Total length of miles of the ASMGHG regions is greater than the total miles because some reaches are in more than one region.

Note 2: Delta WQI values are scenario weighted sums minus baseline weighted sums, so positive values indicate water quality improvements.

regions are likely to be influenced by the compounding factors of other regions. The delta regions may be experiencing the high level of water quality changes as the result of streams from other regions (i.e., the Corn Belt, North Plains and Lake States) flowing into these regions and affecting water quality.

### 3.3.2 Visual Analysis of National Maps

The national and regional level water quality results revealed that the majority of the water quality changes resulting from a carbon pricing incentive policy would occur in four or five of the 10 ASMGHG regions. Figures 3-3 and 3-4 highlight the areas where the greatest changes in water quality occur under the $25/tonne scenario. These areas were identified by locating the highest collections of stream reaches ranging in the top and bottom 5 percent of all reaches in the nation for water quality changes under the pricing scenario. The figures show the RF1 reaches at a much finer level of detail than the previous maps. The regional heterogeneity that has been discussed throughout the water quality
results sections is easily identified in the maps by the reductions (red) and improvements (light and dark blue) in the individual reaches. Visual representation of changes at this scale allows us to see how although some reaches within a region may experience increased loadings and reductions in water quality, improvements in other reaches within the same region outweigh the reductions, resulting in a small improvement in overall water quality. However, we must not over-interpret the microscopic or reach specific details. Aggregated or macro models such as ASMGHG and NWPCAM that are built on micro-level elements or cells are typically more accurate at the aggregate level than at the individual cell. We return to this qualification in Section 4.

### 3.3.3 Case-Study I: The Breadbasket

Figure 3-3 shows the changes occurring in the North Central portion of the U.S. This area roughly represents the Upper Mississippi hydroregion and the southeast portion of the Missouri hydroregion. In the map we see a large number of light and dark blue reaches in the lower portions of Minnesota, Wisconsin, and across all of Iowa and Illinois, or the Upper Mississippi hydroregion. This hydroregion coincides with two of the ASMGHG regions discussed previously, the Lake States and Corn Belt regions. Recall from earlier discussions that these two regions have a high potential for both GHG emission reductions and resulting water quality improvements, as shown by their relatively high co-benefits elasticity.

Figure 3-3 also reveals a large number of reach improvements in North and South Dakota, Nebraska, Kansas, and Iowa. This area is representative of the southeast portion of the Missouri hydroregion and the North Plains ASMGHG region discussed above. Considering the complexities of water quality dynamics, measurement, and modeling, our analysis shows that while there is some reduction in water quality within the “Breadbasket” region, the overall water quality improvements are the highest in the country.

As part of the 1977 CWA requirements, each state must report on the conditions of their streams and lakes (305(b) reporting) to be included in the National Water Quality Inventory Report to Congress, and to help achieve the objectives of the act. These
Figure 3-3. Changes in Water Quality Indices (WQI) by Reach in the Breadbasket Case Study: $25/Tonne Scenario Compared to Baseline

Note: Positive values represent improved water quality.

reports contain information on the current condition of the streams and lakes in the state and the primary causes for their impairment.

It is not surprising to see that the “Breadbasket”, recording the largest improvement in water quality, includes states that report agricultural run-off, including organic enrichment, suspended solids, nutrient enrichment, and pesticides as the primary cause of impairment in their state 303(b) reports. For example, Iowa reported that aquatic life is impaired in 19 percent of the states assessed rivers, and swimming uses is impaired in 54 percent of assessed rivers. The actual percentage of impaired waters could be much higher if all stream miles were assessed.

5For a full report on the condition of Iowa waters please refer to the full 305(b) report http://www.epa.gov/305b/98report/ia.pdf. Each states 305(b) report can be found through the EPA web site http://cfpub.epa.gov/surf/locate/map2.cfm
The 305(b) reports suggest that 20 to 60 percent of the rivers in the “Breadbasket” do not meet their water quality goals, i.e., do not support aquatic life. Our analysis shows that agricultural practices in response to GHG incentives can result in a 5 to 8 percent increase in water quality in this region. Note, these estimates are based on weighted averages for all stream miles in the region and not only on those assessed by the EPA as in the 305(b) reports. Although we know the primary causes of the regional water quality impairments and the predicted improvements based on NWPCAM, we do not have quantitative data to directly assess our predicted improvements in a regional policy context. That is, we do not have information on how much improvement is necessary in the 20 to 60 percent of miles of “dirty” rivers and streams to meet regional water quality thresholds. We can only conclude that there will be a 5 to 8 percent improvement, but not whether these improvements will allow this region to meet its water goals for 100 percent of its rivers and streams.

3.3.4 Case-Study II: The Gulf States

Figure 3-4 shows less dramatic results than Figure 3-3, but contains a large portion of the top 5 percent of improved reaches. This map contains three major hydroregions; the Arkansas-White-Red, the Texas-Gulf, and the Lower Mississippi. These hydroregions map well to the Delta States and South Plains ASMGHG regions, which were shown to have the greatest synergies for co-benefits. The co-benefits elasticity for these two regions was 0.09, and 0.04 respectively.

Again we can see the heterogeneity that exists within regions and hydroregions. Unlike Case Study I where there was an abundance of change occurring, this area shows that the majority of the quality changes are the result of a small number of reaches. The majority of the reaches in these hydroregions experience no change from baseline conditions, however, the reaches that do change experience large improvements. Again, looking at the map we can see that the reaches experiencing the changes are those that are located in areas influenced by agriculture.

---

6Specifically, the percent of rivers not supporting aquatic life uses are 19 percent in Iowa, 28 percent in North Dakota, 64 percent in South Dakota, 23 percent in Nebraska, 27 percent in Kansas, 50 percent in Minnesota, and 47 percent in Missouri.
This case study also lets us comment on the hypoxia problems in the Gulf of Mexico. Hypoxia is a condition of low levels of dissolved oxygen in a water body. This condition is caused by increased levels of nutrients such as N and P in tributary waters. These nutrients often originate from increased agricultural run-off due to the loss of streamside wetlands and vegetation (Goolsby et al., 2000). According to the 1997 Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, an important step in solving the hypoxia problem lies in reducing the hypoxic zone in the gulf to be less than 5,000 square kilometers by the year 2015. To achieve this goal it was estimated the nutrient loadings, especially nitrates, would need to be reduced by 20 to 30 percent (Greenhalgh and Faeth, 2001). Greenhalgh and Faeth report that annual phosphorus
and nitrogen loadings to the Gulf are around 136,000 and 1.5 million metric tons respectively.

Table 3-7 reports changes in N loadings to the Gulf of Mexico. Under the two pricing scenarios, NWPCAM results show a reduction of over 144,000 and 160,000 tons per year, respectively.7

<table>
<thead>
<tr>
<th>TSS</th>
<th>N</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>$25/Tonne of CE</td>
<td>$25/Tonne of CE</td>
<td>$25/Tonne of CE</td>
</tr>
<tr>
<td>8,783,097.58</td>
<td>144,565.31</td>
<td>-728.90</td>
</tr>
<tr>
<td>$50/Tonne of CE</td>
<td>$50/Tonne of CE</td>
<td>$50/Tonne of CE</td>
</tr>
<tr>
<td>9,557,527.36</td>
<td>160,578.29</td>
<td>32.71</td>
</tr>
</tbody>
</table>

Note: Values are reductions in tons/yr. A positive value is a reduction; a negative value is an increase.

Converting the two loadings to equivalent units of measure (1 metric tonne = 1.1022 tons) reveals that the reductions in nitrogen loading resulting from GHG mitigation activities could account for up to 8.7 and 9.7 percent reduction in annual loadings to the Gulf, or nearly one half of the reduction goals established by the Watershed Nutrient Task Force in 1997.

Phosphorous loadings, although generally more of a problem in freshwaters systems, is another common pollutant influencing problems in the gulf. Loadings to the gulf increase slightly under the lower GHG price and then flip to a net reduction of 32.7 tons under the higher price. This reduction however is very insignificant as it offsets less than 1 percent of annual phosphorous loadings to the gulf.

Collectively, these results show that in addition to the water quality co-benefits in the national river networks, reduced loadings into estuaries could result from establishing a GHG market. Although these results predict the level of reduced loading into the Gulf of Mexico, it is beyond the scope of this report and NWPCAM to hypothesize or predict the changes in the quality of the Gulf as a result of the changes in loadings.

7These reductions in loadings account for nitrogen attenuation, or nitrogen loss in waterways in relation to channel width, by using streamflow-dependent first-order decay coefficients derived in the USGS SPARROW model.
Discussion

The analysis described in this report primarily links an agricultural-forest sector model with a water quality model to provide simultaneous estimates of GHG mitigation, sectoral response, regional production, and associated water quality co-benefits under GHG mitigation incentives. The results presented only cover a subset of land use activities (namely agriculture) and water pollutants, yet they suggest that GHG mitigation activities in agriculture can generate water quality co-benefits. The water quality co-benefits are highest in the “Breadbasket” (in absolute) and in the “Gulf States” (proportional to GHG reduction). In many of these states, the agricultural sector has a large economic and environmental presence. Water quality improves in every aggregate region in the country, although the level of improvement varies under the pricing scenarios.¹ These differences in improvement are the result of economic forces re-allocating the more intensive production practices in response to inter-regional comparative advantages in crop production and GHG mitigation. In this section, we discuss the key water quality results, policy prescriptions and important caveats of our analysis.

Figures 3-1 and 3-2 illustrate the nationwide changes in water quality resulting from the GHG pricing scenarios. The map for changes in WQI under the GHG incentives shows much more “texture” as to where water quality changes are occurring than can be shown by tables or graphs. The key results from NWPCAM are as follows:

¹There may well be individual reaches and streams in the RF1 network that suffer water quality impairment.
Nationwide water quality increased 1.38 water quality index points under both GHG pricing scenarios.

Five regions, all roughly East of the 100th meridian (North Plains, South Plains, Lake States, Corn Belt and the Delta States) experienced the largest water quality improvements ranging from about 3 to 8 percent.

“Breadbasket” states (Iowa, Kansas, Nebraska, and the Dakotas) experienced the largest change in water quality, nearly a 4 point improvement.

Gulf States (Texas, Oklahoma, Louisiana, Mississippi, and Arkansas) have the highest co-benefit elasticity, revealing the largest improvement in water quality proportional to the amount of GHG mitigation.

Nitrogen loadings into the Gulf decrease by about 9 percent, whereas phosphorous loadings decrease by less than 1 percent.

4.1 WATER QUALITY POLICY CONTEXT

Although it is not the explicit goal of this analysis to link climate change mitigation policy and the goals of the Clean Water Act (1977), we can qualitatively compare the water quality impacts of climate policies to the goals and past accomplishments of the CWA. Section 1251 of the CWA defines the goal of establishing “boatable and fishable” water quality conditions in the nation’s waters by 1985. However, The National Water Quality Inventory Report to Congress in 1998 reported that about 40 percent of the streams that were monitored by the EPA were not clean enough to be classified as fishable or swimmable. It is clear from these findings that the goals of the CWA have not been met, 13 years after the deadline was established. Our results show that carbon policies can move the nation’s waters—on average—from below swimmable to approximately swimmable levels. It is worth repeating that this is a national weighted average, and clearly specific reaches and rivers will not accomplish this water quality.

Looking specifically at regions, we know that 20 to 60 percent of the miles of rivers in the “Breadbasket” do not meet their water quality goals, i.e., do not adequately support aquatic life. Our analysis shows that agricultural practices in response to GHG incentives can result in a 5 to 8 percent increase in water quality in this region. Although we know the primary causes of water quality problems in this region and the predicted improvements, the regional goals and accomplishments are too generally worded for us
to directly place our results in a regional policy context. That is, we do not have information on how much improvement is necessary in the 20 to 60 percent of miles of “dirty” rivers and streams to meet regional water quality thresholds. We can only conclude that there will be a 5 to 8 percent improvement, but not whether these improvements will allow this region to meet its water goals for 100 percent of its rivers and streams. With regards to the hypoxia problem in the Gulf of Mexico, we find that GHG mitigation activities could reduce annual nitrogen loadings up to 9 percent, or nearly one half of the reduction goals established by the Watershed Nutrient Task Force in 1997. With regards to phosphorous, generally more of a problem in freshwaters systems, we find that GHG mitigation activities will insignificantly reduce phosphorous loadings to the Gulf.

Collectively, these results suggest that regardless of how we disaggregate (hydroregions or ASMGHG regions), GHG incentive policies should primarily target areas East of the 100th meridian and heavily influenced by agriculture to achieve water quality goals. These areas produce the largest reduction in GHG emissions, and although some reach segments realize reduction in water quality, they provide the highest co-benefits in the form of water quality.

4.2 EXPLANATIONS

Consider some important trends and explanations in reviewing these conclusions. As Tables 3-2 and 3-3 and Figures 3-1 and 3-2 illustrate, there is considerable heterogeneity across regions and GHG incentive scenarios in terms of agricultural loadings and in-stream water quality. These heterogeneous results reflect at least two complicating factors. First, variations in regional comparative advantage in agricultural production and GHG mitigation cause inter-regional shifts in production activities in response to the GHG incentives. This reflects the spatial and cross-sectoral equilibrium aspects of ASMGHG. The model allows prices of agricultural commodities to increase as agricultural supply falls because of the change in management practices and land use change. In some circumstances (e.g., Appalachia under the higher GHG price scenario), the indirect response caused by these agricultural price effects may more than offset management responses due to GHG incentives, thereby leading to a net increase in the loadings of some
pollutants. Second, some activities that enhance GHG benefits have some offsetting water quality costs. For example, runoff may increase on converted lands, or greater infiltration of water into soils resulting from increased organic matter and water-holding capacity may over time increase nitrate infiltration into ground water.

Is it possible for pollutant loadings to increase with the GHG incentives? Recognize that establishment of a carbon price is a GHG incentive, not a loadings or WQ incentive. This incentive may cause agricultural practices to change in ways that mitigate/conserve GHGs. In the case of conservation tillage, the synergy is seemingly positive (more carbon in the soil, less erosion (TSS), and perhaps less N, P needed). However, it is also possible that carbon prices cause farmers to switch to crops with higher nutrient requirements and therefore higher runoff. So, on balance, we find positive co-benefits, but this is an empirical finding, not a universal article of truth.

We also find that the higher GHG price did not necessarily generate higher water quality improvements, supporting the theory of diminishing returns mentioned earlier. That is, while the initial GHG reduction results in a significant improvement in the WQI, the larger GHG price improves water quality, but to a lesser degree than the initial impacts. Consider four explanations. First, the direct GHG mitigation effects diminish as we move from the lower to the higher GHG price, so it is not too surprising that the water quality effects are diminishing as well. The second factor relates to the point mentioned in the previous paragraph. The actual commodity being purchased is a reduction in GHG, not water quality improvements. The water quality improvements are a by-product or added benefit resulting from the proposed policy actions of establishing a carbon market. Third, as shown in Figure 2-2, agricultural lands (linked to ASMGHG) are just one from a myriad set of point and nonpoint source loadings into the nation’s waters. The additional ASMGHG loadings are insufficient to cause additional water quality changes. Fourth as the GHG incentive price rises more land is diverted from traditional agricultural production to biofuels, forests, and grasslands. The remaining crop land is farmed more intensively with increased inputs and this tends to moderate the water quality gains.
The Gulf States show the greatest synergies (highest co-benefit elasticities) probably because the rivers flowing into the Gulf are the receptacle for the country’s primary agricultural lands, being at the lowest point in the hydrologic network. These rivers accumulate the improvements in water quality in all upstream regions, including the main agricultural zones—Corn Belt and North and South Plains. Some portion of the water quality improvements in the Delta and South Plains region may well be in response to GHG mitigation practices, but these are not separable from those resulting from the impacts of other regions.

### 4.3 QUALIFIERS AND EXTENSIONS

It is critical to review some qualifications to the analysis and results presented in this report. Perhaps the biggest temptation is to view Figures 3-1 through 3-4 as a source of microscopic or reach specific detail. We must recognize the inherent traits of models such as ASMGHG and NWPCAM that are built on micro-level elements or cells. Projections and output from these aggregated models are more accurate at the aggregate level than at the individual cell. This is because the macro models are relying in a sense on the “law of large numbers” such that averages are reasonably accurate, without any guarantees for detailed output. In other words, we can assume that pluses and minuses cancel, so that averages are roughly correct. This qualification does not imply that the modeling exercise described in this report is not credible. Instead, it suggests that the processes and outputs holds at the macro level (in this case national and regional) and provide first-order estimates of policy induced GHG and WQ changes.

Additionally, there are factors outside these model results that may have important environmental consequences. For example, increased carbon stocks, conversion of lands to grassland and increased reliance on biofuels are some of the inherent results of the changes in the management of agricultural lands with the new GHG prices. These actions and associated results may increase long run soil productivity as they may increase its ability to retain nutrients and moisture, thus reducing the reliance on fertilizers and increasing its resistance to drought by reducing water requirements. Moreover, changes in land use and land management can alter the biodiversity of the landscape’s flora and fauna. The potential for
these additional co-benefits are important factors to be considered in future analyses.

Finally, we must remember that currently ASMGHG does not account for any loadings that may occur as a result of forestry activities. Moreover, publicly available and reliable livestock data are not available to evaluate the impacts of livestock activities. Insufficient data and resources did not permit us to spatially disaggregate and model manure and forestry loadings. It is unclear whether the net result of including these loadings would increase or decrease water quality in the net. For forestry, when ASMGHG projects afforestation, for instance from cropland to forest, then all of the loadings that would have occurred on the cropland are eliminated from the model output. This is tantamount to saying that the forestland generates no loadings. On the other hand, we overlook all improvements in water quality from reductions in livestock herds. Our priors are that the changes in manure loadings have a greater effect on water quality than runoff from forests, but the relative amount of change in each category should be considered because it varies widely.

Although the study was successful in accomplishing its primary objectives, two areas warrant further attention in future research. First, it could be critical to evaluate how loadings from livestock manure and afforestation influence the overall water quality results. Second, it would be informative to monetize the co-benefits. Such monetized estimates would allow us to evaluate whether the benefits of water quality improvements sufficiently supplement GHG mitigation benefits to offset, or possibly outweigh, the cost of carbon payments.

### 4.4 SUMMARY

In summary, claims of extensive and prevalent co-benefits (e.g., quality of soil, water, air, and wildlife habitat) of GHG mitigation policies have not been backed up by rigorous quantitative analyses. This study develops first order estimates of water quality co-benefits by linking ASMGHG—a national model that estimates changes in land use and management, GHG emissions, and pollutant loadings in response to GHG price incentives—with NWPCAM—another national scale model that estimates pollutant fate, transport, and decay in the nation’s waters resulting in overall impacts on water
quality. Prices of $25 and $50 per tonne of carbon equivalent are introduced in ASMGHG, which induces changes in cropping, management (e.g., conventional to no-till agriculture) and land use (afforestation). Based on ASMGHG output in terms of changes in agricultural loadings of nitrogen, phosphorus, and erosion or total suspended solids, NWPCAM predicts national water quality (measured using a single index). We measure overall economic and ecological impacts of GHG mitigation policies in terms of changes in economic welfare, LULC, GHG emissions, and water quality. Specifically, we find that the largest water quality improvements are found in the “Breadbasket” and Gulf States of the U.S. Our results show that GHG mitigation policies, which would cause 6–13 million acres to leave agriculture, can improve the nation’s waters quality by an average of 1.38 points on the water quality index. Additionally, GHG mitigation activities could reduce annual nitrogen loadings into the Gulf of Mexico by up to one half of the reduction goals established by the Watershed Nutrient Task Force for solving the hypoxia problem.
References


