

Nonpoint Source Pollution Mitigation Through Tax under Climate Change

1. Introduction

Will climate change make the already daunting task of reducing nonpoint source pollution (NPS) even more difficult? The speculation seems well founded, given the fact that agriculture is the largest contributor of NPS water pollution and the possibility of continuous intensification to combat the potential adverse effect of climate change on crop yields (Shortle et al., 2021). Indeed, the existing literature almost unanimously suggests an escalating challenge posed by climate change, attributed to harder-to-achieve mitigation benchmarks (Metaxoglou & Smith, 2022; Renkenberger et al., 2017), less effective abatement practices (Lintern et al., 2020; Qiu et al., 2020), and larger uncertainties associated with extreme weathers (Kamrath & Yuan, 2023). Most of these studies employ sophisticated process-based models like SWAT to simulate hydrological and biological processes altered by climate variables and abatement practices (Plunge et al. 2023; Xu et al. 2019), but pay much less attention to economic factors such as market reactions to climate change and decision-focused economic optimization (Bosch et al. 2018). Excluding behavioral changes from the assessment fails to provide a holistic view of the climate impact on NPS management. To overcome this drawback, more studies start to embrace the approach of integrated assessment models (IAMs), which are designed to capture the linkages and feedbacks between multiple systems, particularly between socioeconomic and biophysical processes (Parson & Fisher-Vanden, 1997).

Despite the promising progress, many technical obstacles remain that potentially compromise the overall performance of the IAMs due to the estimation error arise from ignoring the spatial patterns within administrative boundaries, and event give mis-leading results in case that what the policy prescription tries to seek is spatial targeting or customized solution. Bearing these challenges in mind, our study answers the following objectives: (1) Quantify local impacts of climate change on crop yields and N loss using an agro-ecosystem model Agro-IBIS; (2) Condense the output of Agro-IBIS into transfer functions and use them to connect Agro-IBIS with an economic equilibrium model SIMPLE-G; (3) Apply the integrated modeling system to a hypothetical N tax policy and assess how the cost and efficiency of market-based policies will be affected by climate change; (4) Demonstrate the value of fine-scale IAMs for nutrient management policy design in terms of providing empirical basis for spatial targeting and pollution evaluation.

2. Methods

Figure 1 provides a depiction of the integrated modeling framework and the experimental design. The first step is to use Agro-IBIS model to simulate yields and N losses responses to various rates of N fertilizer application. We select climate projections from three GCMs (GFDL-ESM2M, HadGEM-ES365, CSIRO-Mk3-6-0), and for the historical period of 1950 to 2005 as well as RCP 4.5 and 8.5 for 2006 to 2050. Then we fit Gompertz curves to the yield responses to obtain yield transfer functions and fit quadratic curves to the N loss responses to obtain N loss transfer functions. These grid-specific transfer functions allow us to compute the shocks to crop yields and N loss, which we use to perturb the SIMPLE-G model for baseline updating. The

new baseline mimics the economy under climate change, where farmers perceive the yield impact of climate but meanwhile maintain the same level of output through intensification and extensification. Out of this step, we obtain the price ratio between crop and N fertilizer that can be used to solve for the economically optimal N application rate based on the first order condition of the optimization problem. Because the yield shocks are calculated assuming constant N application rate, whereas in reality the application rate does change as a practice of adaptation, the yield shocks alone may not fully reflect the actual impact of changing climate. Therefore, we introduce an additional shock to the productivity of N fertilizer as a remedy for this discrepancy. The shock is calibrated by perturbing the N application rate in SIMPLE-G by the amount informed by the previously calculated change in the economically optimal N application rate. We then carry this N productivity shock in the policy analysis to capture the impacts of climate in full but avoid dictating N application.

At the end, we study an N loss tax policy that charges higher tax rates for heavily polluting farms. A previous study (Liu et al., 2023) found that under current climate condition, a \$1/kg of N loss tax that increases fertilizer price by 30% reduces total N loss from US corn farms by 9%, or 0.33 million metric tons. By rerunning this experiment under the new climate, we make the tax endogenous and use it to target the 0.33 million tons of N loss reduction, then compare the updated tax with that in the previous study.

3. Main findings

First, we find that future climate change will likely affect crop yields and N loss negatively but the impacts vary by location and farming practices. The impact is generally larger under the higher forcing scenario. For example, the median yield impact for rainfed crops under RCP 8.5 is -12.5%, which is stronger than the median yield change of -8.1% for RCP 4.5. Rainfed crops suffer more than the irrigated. The density distribution of the yield change is bimodal for the irrigated crops with distinct peaks near +10% and -5%, but almost unimodal for the rainfed crops with a peak near -10% (Figure 2).

Second, under future climate, crop price may rise faster than the price of N fertilizer, leaving room for continuous intensification while remaining profitable. Using the baseline crop price and N fertilizer price that are \$4.6/bu and \$1.5/kg, we estimate the price ratio of N to crop P_N/P_{crop} to be 0.132 in the baseline, but it falls to 0.124 and 0.115 for the RCP 4.5 and RCP 8.5 scenario, respectively. A lower price ratio means that crop price increases more than fertilizer price, allowing for further fertilizer intensification. We also see a larger increase in N loss (+30%) than the increase in N application (+15%), due to the shape of the quadratic N loss function as well as the altered spatial distribution of the production that potentially pushes production into locations where land used to be laid fallow due to low productivity or high pollution. Bringing these lands back to cultivation requires more supplemental nutrient and also increases the average intensity of N loss.

Finally, we find that the cost of reducing the same amount of N loss will increase under warmer climate. Specifically, the N loss tax rate increases from \$1 to \$1.3 and \$1.7 /kg of N loss under the RCP 4.5 and RCP 8.5 scenario. Reducing the same amount of N loss costs 3.5 billion USD previously but increases to 4.9 and 6.6 billion USD in the wake of climate change. The abatement cost also increases from \$10 to \$14 (RCP 4.5) and \$20 (RCP 8.5) to reduce one kilogram of N loss from corn production in the US.

4. Discussion and conclusion

Climate science has advanced significantly in the past decades but the new science has not been fully and properly reflected in the economic assessment of the social cost of carbon and nitrogen. In this study, we present a novel way of using transfer functions to connect an agro-ecosystem model with an economic model at the fine-scale and improve the scientific basis of integrated assessment modeling and analysis. The employment of transfer functions permits us to explore the yield and N loss responses across the whole spectrum of meaningful application rates, instead of looking at the impact at a specific application rate. We find that simultaneously improving food security and environmental stewardship may face a greater challenge under future climate due to both the higher opportunity cost of conservation and a larger mitigation target. Our study provides empirical basis for NPS pollution control policies. For instance, the economic optimal N application rate informed by the transfer functions can supplement the “Corn Nitrogen Rate Calculator” tool that serves the same purpose of finding the maximum return to N but only available for seven states and for a couple of regions within each state. The site-specific N loss intensity provides practical guidance to prescribe a tax with variable rates for targeting.

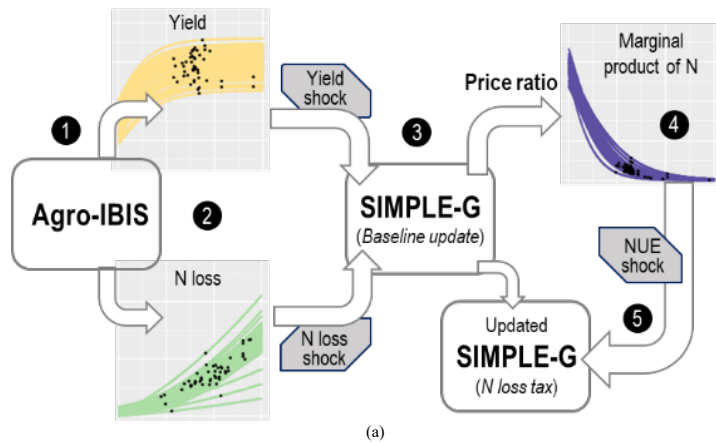


Figure 1. Integrated modeling framework and experimental design.

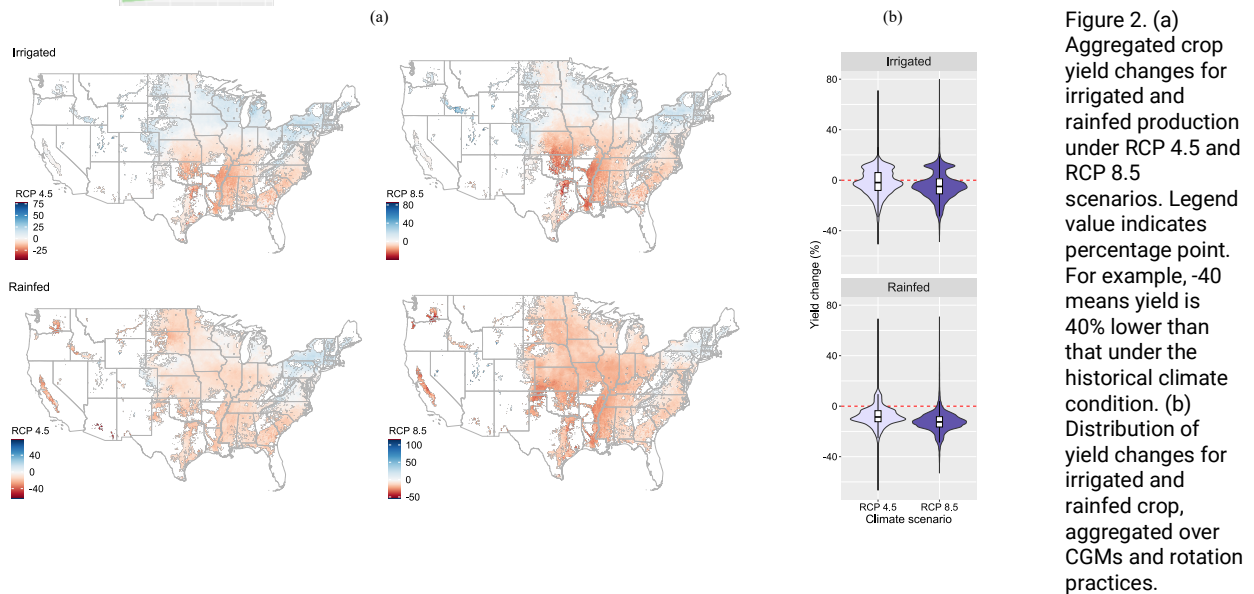


Figure 2. (a) Aggregated crop yield changes for irrigated and rainfed production under RCP 4.5 and RCP 8.5 scenarios. Legend value indicates percentage point. For example, -40 means yield is 40% lower than that under the historical climate condition. (b) Distribution of yield changes for irrigated and rainfed crop, aggregated over CGMs and rotation practices.