Damages of Surface Ozone: Evidence from Agricultural Sector in China

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Abstract:

This study measures the damages that surface ozone pollution causes within the Chinese agricultural sector. We find substantial spatially differing damages that are greatest in wheat growing areas with higher ozone concentrations. The total damage in China's agricultural sector probably ranges between CNY 1,630 billion and CNY 2,238 billion, which accounts for one fifth of agricultural revenue in 2014. A moderate ozone reduction by 30% benefits the agricultural sector by CNY 678 billion. The benefits largely fall to consumers with producers losing as the production gains lead to lower prices lessening food costs and simultaneously farm income.

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Keywords: Surface ozone; agricultural sector; marginal damage

1 Introduction

Ozone is damaging to agricultural yields, causing substantial crop losses particularly for wheat and rice (Adams, 1983, Heck, et al., 1982). Regionally China has areas with high ozone concentrations but discussion of ozone pollution damages largely centers on human health concerns with little attention paid to agriculture. Not much is known on the total extent of Chinese agricultural ozone induced crop losses and the associated welfare losses. This paper reports on an attempt to quantify the total physical and economic agricultural damages plus explores the benefits of reduced ozone levels.

A few agriculturally related ozone control studies have examined the potential benefits of reducing ozone concentrations to specific levels (Adams, et al., 1982, Adams, et al., 1985, Kopp and Krupnick, 1987). These studies measured the average value of damages of surface ozone pollution. Muller and Mendelsohn (2007) pointed out it would be better to estimate marginal rather than average damage measures arguing employing marginal values provides a sound way to measure the marginal benefits of controlling pollution, especially considering that these values can be compared with marginal abatement costs to guide regulators toward more efficient policies.

In this study, we estimate marginal damages and total loss following the suggestion by Just, et al. (2005) that a mathematical programming model be used over systematically varying pollution levels.

2 Methodology and data

The framework we use to estimate the marginal agricultural damages of altered surface ozone involves several components. First, we present a guiding theoretical framework. Second, we select functions that give ozone damages on predominant Chinese crops from peer-reviewed studies. Third, we construct spatially disaggregated empirical marginal damage estimates using a China agricultural sector mathematical programming model. This process allows us to link changes in surface ozone pollution with marginal consequences in the agricultural sector and in turn levels of damage.

2.1 Theoretical framework

Let us now form a simplified model of farm losses from ozone. Suppose in producing goods farmers operate so as to maximize profits and that profits are influenced by level of surface ozone exposure e. In maximizing profits assume farmers can employ a number of production possibilities (z) the results of which are influenced by ozone concentration $z(e)$. The function $\Pi(z(e^0))$ denotes profits given an initial ozone level of e^0 without pollution control policy. Now suppose we wish to reduce ozone concentrations by a, in turn optimal profits decision can be expressed as

$$\max_{z} \quad \Pi\big(z(e)\big)$$

$$\text{subject to} \qquad e \geq e^0 - a \qquad [\lambda] \quad , \qquad (1)$$

where λ represents the associated marginal damage of ozone exposure. The marginal damage in agricultural sector can be calculated as

$$MD(e) = -\frac{\partial \Pi^*}{\partial z} \cdot \frac{\partial z}{\partial e} = \lambda \geq 0 \,. \qquad (2)$$

This marginal damage function represents a relationship between the ozone concentration level and the damage caused by the pollution. This gives an upward-sloping damages curve as concentrations increase, and the area below the function measures the total damage. Now, the marginal benefits of reducing the ozone level derived from Equation (2) can be compared with marginal abatement costs (MAC) to guide regulation toward efficient policies if MAC is available.

2.2 China agricultural sector model

To estimate the marginal damages curve we developed a multiple-region, multiple-commodity price endogenous, partial equilibrium model, hereafter called the China Agricultural Sector Model (CASM)[1]. CASM is a bottom–up, mathematical programming model that represents the monthly production of primary agricultural products over growing seasons across all of China. CASM reflects national markets and regional resources. The basic structure of the model is discussed in McCarl and Spreen (1980) and with an implementation discussed in Beach and McCarl (2010). CASM has 365 subregions within Mainland China that surround prefecture-level cities. Each subregion possesses differing endowments of arable land and labor along with varying cropping and livestock mixes with different production budgets reflecting both heterogeneous production possibilities and resource endowments across China. Cropping patterns in each subregion are independently and portrayed by representative farm models. These models are assumed to mimic the technical and economic environment for producers in each subregion as discussed in Adams, et al. (1986). The objective function of the model is to maximize the area under the demand curves less than the area under the supply curves.

CASM gives an aggregate representation of the Chinese agricultural sector and needs to be structured so it adequately represent that sector. To do this we will form the model as above but then calibrate it to match observed production and consumption data. To achieve this we employ the positive mathematical programming (PMP) approach developed by (Howitt, 1995) that manipulates the form of the production costs in an effort to replicate observed cropping patterns and numbers of livestock in 2014. Data availability restricts us to use the classical form of PMP as opposed to more recent version that employ more

[1] Appendix A discusses CASM in detail.

flexible production functions (e.g., generalized constant elasticity of substitution functions-(Graveline and Mérel, 2014, Mérel and Bucaram, 2010, Mérel, et al., 2014). In particular, we use the classic quadratic form and calibrate against observed production levels.

CASM results on commodity production and prices closely match the observed data. Table 1 presents comparisons of 2014 actual and model prices and planted areas generated from the calibrated CASM. The crop and livestock prices and quantities are within 5% of the actual 2014 observations. We believe that this shows CASM is suitable for further analysis.

2.3 Deriving crop yield ozone effect

To examine the effects of ozone on agriculture, we need functions explaining the relationship between ozone and yields. Such functions are called dose-response functions. The basic ozone dose response functions we use come from Mills, et al. (2007) which used in a number of studies including Chuwah, et al. (2015).

An ozone exposure metric is needed to use the Mills, et al. (2007) functions and several forms of this have been used. These involve three cumulative exposure metrics (*AOT40, SUM06*, and *W126*) and two mean exposure metrics (*M7* and *M12*) (see the definitions in Appendix B). The use of a mean concentration implicitly endows equal weights to all concentrations and disregards the length of exposure (Fuhrer and Booker, 2003). Accumulated ozone concentrations exceeding a threshold over growing season are considered better representations of the influence of ozone on crop loss as opposed to indices relying on seasonal mean or peak ozone concentration (Mauzerall and Wang, 2001). Among the exposure-based ozone indices, *W126* is generally viewed as a superior representation of forces creating observed yield loss but is more difficult to implement as a regulatory standard. *AOT40* has been used most widely in the last two decades in dose-response functions (Mills, et al., 2007, Tang, et al., 2013) and will be used here.

A lack of data on radiation raises difficulties in creating *AOT40* values. In particular, the formula needs a measure of whether daily radiation is more than 50 Wm^{-1}. Ignoring that factor leads to an overestimate of *AOT40*. Thus, we use the method suggested by Mills, et al. (2007) to estimate *AOT40*. They used an empirically estimated function to convert a three-month *M7* (ppb) to *AOT40* (ppm). The fitted function can be expressed as

$$M7 = 29 + 1.59AOT40 \quad . \qquad (3)$$

The regression with a high level of goodness of fit suggests a reliable means to generate *AOT40* observations.

Another challenge is that ozone effects on many crop species have not been investigated in China. Thus, we used dose-response functions estimated in the European Union or the United States. Previous studies show insignificant differences for soybeans, wheat, and corn (Adams, et al., 1986, Heck, et al., 1984). Therefore, this study implies pooled-response functions for all cultivars for each crop. The full list of the functions used is presented in Appendix C. Over all, wheat is the most ozone-sensitive grain crop.

For most of the crops modeled in CASM, we applied the dose-response functions from Mills, et al. (2007). For sugarcane and peanuts, no suitable dose-response functions were found in the literature. However, González-Fernández, et al. (2008) and O'Connor, et al. (2003) reported that both of these crops exhibit sensitivity to ozone similar to that of cotton. Therefore, we used the cotton dose-response function for sugarcane and peanuts. To cover all crops modeled in CASM, we used the dose-response functions of barley to represent all other grains, pulses to represent other beans, and broccoli to represent fiber crops. We also used the average functions for tomato, turnip, onion, and lettuce to represent all other vegetables.

2.4 Methods used to estimate damages

In order to estimate damages we plug estimates from the dose response functions into CASM. In doing this we assume that the ozone imposes a neutral technological change following Adams, et al. (1986). With input levels assumed unchanged, we will reduce yields by the percentage change in crop yields forecast by the dose response functions under base ozone levels versus an alternative level. In turn CASM is first applied to compute baseline welfare at 2014 ozone levels.

Now we turn to the procedures used to construct the estimates of the marginal ozone damages/benefits caused by increasing or decreased levels. In doing this we follow suggestions in Muller and Mendelsohn (2007) and develop a series of steps over a range of escalating or declining ozone levels. First, we successively solve CASM under conditions where we reevaluate the crop yield estimates with a series of higher/lower ozone levels for every crop in each subregion and plug those into CASM then collect the results on welfare. Then, we compute marginal damage by subtracting the ozone-impacted welfare from the baseline welfare. This procedure is repeated for each of 365 subregions to generate regional marginal damages in ozone exposure of 2014 for alternative ozone levels ranging from -20ppm to +10 ppm in 1-ppm steps. An important feature of this design is that it yields spatially differentiated estimates of the marginal damages from ozone thus identifying the most impacted regions.

After obtaining marginal damages estimates over the range of ozone exposure levels across the 365 subregions, we adopt a summary function approach (Griffin, 1977, Preckel and Hertel, 1988) to summarize the level of aggregate damages by subregion and later nationally. Considering the heavy computation burden, we first develop regional estimates of marginal damages at $i = 1, \ldots, 30$ for 30 added ozone concentration levels. Second, we fit a summary marginal damage function using econometric methods. The functional form used in the estimation is

$$MD_{ri}(O_{ri}) = f(O_{ri}|\boldsymbol{\beta_r}) + \varepsilon_{ri} \ , \qquad (4)$$

where $MD_{ri}(O_{ri})$ represents the i^{th} observed marginal damage driven by one unit ozone increment from a pseudo ozone concentration level (O_{ri}) in subregion r . $\boldsymbol{\beta}$ is a parameter vector to be estimated by using a minimum sum of squares of the residual criterion, which was also used by Maddala and Roberts (1980) and Preckel and Hertel (1988). The functional form $f(\cdot)$ is a polynomial. The residual term ε_{ri} depicts the approximation errors and could stem from not having the correct function form and measurement errors (Maddala and Roberts, 1980). To simplify the estimation, we invoke the central limit theorem for ε_{ri}. Finally, we integrate the area below the marginal curve estimated in Equation (4) to compute the total damages.

Aside from calculating the aggregate damage relationship using marginal information in each subregion, this study computes provincial marginal damages then constructs a national agricultural damage summary function. This method first uses the CASM estimates at the 365 subregion level to form subregional marginal damages. Second, we construct provincial level results by adding up the result at each ppm level across all subregions falling into each of 31 Chinese provinces/municipalities. Third, we estimate a national summary function as above to compute the total damage functions by province. Even though this method does not allow heterogeneous subregional marginal damages, we believe the setting is consistent with China’s environmental governance strategy.

Next, we perform sensitivity experiments using CASM to portray the economic changes from reducing ozone concentrations from the baseline level for alternative reduction scenarios, namely, 15%, 30%, and 45%. We also examine the distribution of welfare between producers and consumers, and regional gains from ozone reductions.

Finally, we investigate provincial differences in economic gains and increased production. Typically, large-scale studies can obscure significant differences in the regional effects of ozone because of both regional variations in ambient ozone levels and variations in the importance of ozone-sensitive crops produced in the region (Mauzerall and Wang, 2001). The study on the regional basis will identify the most damaged areas and potential targets for ozone control policy.

2.5 Information sources for CASM specification

In CASM, there are 16 primary field crops and 6 livestock types produced regionally when local conditions are allowed. The regional crop and livestock production budgets as well as farm gate prices were obtained from the Data Compilation of China Agricultural Product Cost and Revenue. The agricultural commodity trade data were from USDA. The data on crop planting and harvest time were obtained from both the USDA report on Major World Crop Areas and Climatic Profiles and agronomists' suggestions, if needed. The cost of storage for major commodities were from Chen (2007). Labor supply elasticities were from Feng and Zhang (2012) and are assumed equal across all regions. The demand elasticity data for primary products were adopted from Zhang (2004). All of the prices are deflated to 2000.

Ozone exposure information is obtained from China National Environmental Monitoring Center, which provides hourly ozone observations recorded in 1412 stations located in 338 cities for 2014. To blend all observations to city-level data, a spatial interpolation method was used. In that method, the inverse distance weighted method was applied to interpolate the ozone data from all the air quality monitoring stations across the whole nation to a 1-kilometer grid. Second, the values of each grid located in a city were averaged to represent the mean status of each city. We probably underestimate ozone concentrations for agricultural production because there is evidence to show that surface ozone concentrations in rural areas are higher than those in urban areas (Wang, et al., 2007).

3 Results

3.1 Surface ozone damages

To select the appropriate functional form for the summary functions (4), we use the shape suggested by an examination of Figure 1. That figure shows that marginal damages increase at an increasing rate as surface ozone concentrations increase. Thus, we decided to use a quadratic functional form to estimate $\boldsymbol{\beta}$ in Equation (4). Technically, we estimate $MD_{ri}(O_{ri}) = \hat{\beta}_{r0} + \hat{\beta}_{r1}O_{ri} + \hat{\beta}_{r2}O_{ri}^2 + \hat{\varepsilon}_{ri}$ [2]. Both the extremely narrow 95% confidence interval in Figure 1 and the high levels of R^2 of the estimated summary functions (around 0.99) indicate that summary functions effectively represent the marginal damages estimates as simulated by CASM. Thus, we believe that the estimated summary functions generated from the CASM results can be used in aggregate damage computation.

Figure 2 illustrates spatial differences in the marginal damage estimates across regions in China. Generally, we found significant disparities across seven major regions. For example, marginal damage in East China is more than four times of those in Northeast China even though both regions are major agricultural production areas. The overall economic value of ozone reduction are largest where exposures are high and the region has significant crop production (Westenbarger and Frisvold, 1995). The regional differences are due to the varying cropping pattern, land area farmed, and ozone level. As the most ozone-polluted and wheat-dominated (the most sensitive crop) area, which contributes over 38% of domestic wheat supply, agricultural areas in East China suffer the most from ozone pollution. Northeast China that only contributes 0.39% of domestic wheat supply faces relatively smaller impact. In Northeast China and South China, the ozone concentrations are lower plus rice (a less ozone-sensitive crop) accounts for more than 30% of planting areas in both regions. The above results generally show heterogeneous damages across regions, and suggest spatially differentiated ozone pollution control policies might be attractive.

Table 2 present ozone damage estimates arising at the 2014 levels. Total country

[2] Detailed regression results are available upon request.

wide agricultural damages are estimated at CNY 1,934 billion, which accounts for approximately 0.8% of total sectoral associated welfare, and is of the size of 19% of the country wide agricultural revenue in 2014. Table 2 also shows the 95% confidence interval lower and upper bounds for welfare. Therefore, the total damage estimate falls in the range between CNY 1,630 billion and CNY 2,283 billion, and accounts for a total economic surplus at most of about 1%.

The second row of Table 2 reports a less accurate national measurement of aggregate damages formed by adding up provincial marginal damages. Even though this method is not as precise as the above one, it may be attractive for provincial government for having a rough estimate of the benefits if a uniform ozone reduction is applied within a province. Notably, this value (CNY 1,559 billion) is smaller than the summary function results estimated directly over the CASM subregional marginal damage estimates. The difference could be explained by the fact that the uniform experiment does not capture the differences in marginal damages associated with various subregions as they are given the same weights. Additionally the number of subregions with less marginal damages is relatively more than the number of subregions with higher damages. Thus, average damage estimates are somewhat lower. In addition, the confidence interval of the total damage is smaller than the one adding up all 365 subregions. This result can be explained by the fact that the summary function using provincial averages endows less variation than the estimates using the 365 subregional results.

The third row of Table 2 presents aggregate damages constructed following procedures in Muller and Mendelsohn (2007). Namely we multiply the marginal damage at a concentration level in 2014 by the total ton of ozone emissions, divided by 2 yielding an estimate of the area below the linear marginal damage line. Figure 2 has shown the concavity of marginal damage curves. Therefore, Muller and Mendelsohn (2007)'s method is likely to overestimate the aggregate damages. Thus, the total damage on the basis of linear assumption is CNY 2,165 billion, which is approximately 24% more than the measures based on the quadratic summary function. This finding confirms increased marginal damages at an increasing rate along the increments of surface ozone exposures from Figure 2.

We feel the aggregate damage estimate is a reliable estimate of the actual total damage. We compute the total damage by subtracting the welfare under the exposure of ozone pollution in 2014 from the one without ozone exposure. By using this direct gross damage measurement, the actual total damage is CNY 1,899 billion, indicating that our marginal-damage method has minor 1.8% measurement error. The error can be attributed to the summary function approach. However, this method endows a significant improvement comparing with the one using a linear marginal damage assumption suggested by Muller and Mendelsohn (2007), which has a measurement error about 14%.

3.2 Benefits of surface ozone control

Table 3 shows estimates of the benefits of reducing surface ozone to the agricultural sector. A 15% reduction in ozone concentration entails a gain of CNY 359 billion. Additional ozone reductions of 30% and 45% increase the agricultural benefits but at a diminishing rate. Combining with the total damage reported in Table 2, ozone reduction of 15% eliminates 19% of the damages, 30% eliminates 35% and 45% eliminates 50%. The decreasing marginal benefit of ozone control is consistent with the finding of Adams, et al. (1982).

Our results can be compared with estimates from other studies. Table 3 breaks down the producer and consumer impacts relative to Adams, et al. (1982) and Adams, et al. (1986). Consumers benefit from the increased supply of agricultural products driven by the ozone reductions. However, producers are damaged by the ozone control as the lower concentrations cause increased yields and total supply which leads to lower prices and lower net incomes which was not found in Adams, et al. (1982) and Adams, et al. (1989) but this is a common finding is say climate change studies as discussed below. Clearly, the net impacts of surface ozone pollution control on farmers are determined by the tradeoff between increased agricultural production and price decreases for agricultural products. The change in the magnitudes of producers' surplus and consumers' surplus indicates that the gain for consumers markedly dominates the loss to Chinese farmers much as found in the climate change case by Adams, et al. (1990) and Reilly, et al. (2003). In addition, these results show that lower-income consumers, typically living in urban areas, are likely to be the major beneficiaries of surface ozone control.

Table 4 presents the provincial benefits at different ozone reduction levels. Most of the regions benefit from ozone reductions. With a moderate 30% ozone reduction Hebei, Henan, Jiangsu, and Shandong gain more than CNY 50 billion just in agriculture neglecting health benefits, because these regions have the largest number of residents in China. In Guangxi and Hainan, however, the loss of producers' surplus exceeds the gain for consumers. This shows there will be differential regional effects of ozone control policy.

3.3 Impacts on domestic grain production

Food security is an important concern. Table 5 presents the impacts of surface ozone reduction on domestic grain production. Generally, a decrease in surface ozone increases production of rice, wheat, and maize. Specifically, a 45% reduction generates an additional 92 million tons of grains or about 17% of 2014 supply. Wheat gains account for more than 86% of the total increase, and maize accounts for 13%. On the other hand, rice production decreased slightly when the surface ozone was reduced by 15%, and then increased marginally with larger decreases of ozone exposure. These results suggest that ozone control generally increases wheat and maize supply, but will not substantially change the rice supply.

Table 6 presents the geographic distribution of grain output changes. Hebei, Henan, Jiangsu, and Shandong experience the greatest grain supply increments. In three provinces of Southern China (Guangdong, Guangxi, and Hainan), where rice is a dominant crop, the grain outputs exhibit a small decrease.

Columns 3, 5, and 7 of Table 6 identify the regions with the greatest increase in grain production due to ozone control. These regions currently have fairly high ozone concentration levels and are dominated by ozone-sensitive crops, such as wheat. With a moderate level of ozone reduction (30%), Shaanxi, Tianjin, and Gansu are the most affected regions. Some other regions, like Heilongjiang, Hunan, Jiangxi, Qinghai, and Tibet, experience almost no impact from ozone controls because of their relatively low ozone concentrations and/or cropping patterns dominated by crops not greatly impacted by ozone.

3.4 Discussion on surface ozone control policy in China

This study finds substantial agricultural benefits arise from ozone control along with lower food prices that would benefit the urban poor. These estimates can be weighed against the costs of control policies in a policy setting environment. Also we note these are only partial estimates with control also yielding health and other benefits. China has begun to control ozone by regulating VOC and NO_X ozone precursors. Table 7 shows estimates of the damages in the agricultural sector. The lower bound on these damages is approximately CNY 58 billion, which accounts for 3% of gross damage. The upper bound of charge is around CNY 1,205 billion, which is 69% of gross damage.

A number of factors such as temperature, water vapor, precipitation, cloud cover, wind speed, and mixing depth, also play significant roles on ozone formation and depletion in the boundary layer. Climate change induced by greenhouse gases will affect these items and has been asserted to be ozone increasing with damages rivaling the other potential agricultural climate change effects (Lobell and Asseng, 2017). Given the evolution of climate change, the ozone control effort has to be a dynamic standard rather than a fixed one.

4 Conclusions

This study has assessed the monetary and production impact of ozone pollution on China's agricultural sector. Findings show significant negative impacts in a pattern that varies spatially. The regionally varying damages suggest that regionally targeted policies could address the most damaged areas in a beneficial way. In addition, the result show ozone suppresses food production and that ozone control could help in improving food security particularly for wheat.

This study further finds that Chinese agricultural sector is damaged by surface ozone concentration levels. Our estimates of the range of total damages falls between CNY 1,630 billion and CNY 2,238 billion, which accounts for a total economic surplus of about 1% at most. A moderate ozone reduction by 30% will bring economic surplus increases in the agricultural sector by CNY 678 billion reducing the damages by 35%. Consumers are the main beneficiaries of reductions, while producers lose. Those losses occur because the decreases in product prices more than offset the increase of supply. For the food security concern, wheat in traditional major grain production provinces is strongly increased under ozone control with corn increased somewhat and rice unaffected.

Furthermore the damages estimate herein is conservative as it only covers marginal damage in the agricultural sector neglecting effects on human health and other sectors. Second, we feel there are underestimates of ozone exposure in many rural areas which also make this a lower bound. Third, the lack of information on crop sensitivity in China also biases out estimates of the crop losses and the corresponding damages but we are unsure of the direction. However, our estimates show there are substantial potential benefits from reducing ozone concentrations. This coupled with the ozone increasing expected consequences of climate change suggest the damages may get worse in the future and suggest both starting now and having yet stronger policies in the future.

Methodologically the study uses a country-wide model coupled with literature based ozone dose response functions then generates a marginal damages curve varying zone levels regionally. It then uses a summary function approach that indicates increasing damages as concentrations increase. We feel this is an advance relative to the previous studies in that the marginal damages, the regional estimates and the summary function approach create policy relevant regionalized and summarized results.

References

Adams, R.M. 1983. "Issues in assessing the economic benefits of ambient ozone control: some examples from agriculture." *Environment international* 9:539-548.

Adams, R.M., T.D. Crocker, and N. Thanavibulchai. 1982. "An economic assessment of air pollution damages to selected annual crops in Southern California." *Journal of Environmental Economics and Management* 9:42-58.

Adams, R.M., J.D. Glyer, S.L. Johnson, and B.A. McCarl. 1989. "A reassessment of the economic effects of ozone on US agriculture." *Journal of Air Pollution Control Association* 39:960-968.

Adams, R.M., S.A. Hamilton, and B.A. McCarl. 1985. "An assessment of the economic effects of ozone on US agriculture." *Journal of the Air Pollution Control Association* 35:938-943.

Adams, R.M., S.A. Hamilton, and B.A. McCarl. 1986. "The benefits of pollution control: the case of ozone and US agriculture." *American Journal of Agricultural Economics* 68:886-893.

Adams, R.M., C. Rosenzweig, R. Peart, J.T. Ritchie, and B.A. McCarl. 1990. "Global climate change and US agriculture." *Nature* 345:219.

Aunan, K., T.K. Berntsen, and H.M. Seip. 2000. "Surface ozone in China and its possible impact on agricultural crop yields." *AMBIO: A journal of the human environment* 29:294-301.

Beach, R.H., and B.A. McCarl. 2010. "US Agricultural and forestry impacts of the energy independence and security act: FASOM results and model description." *Research Triangle Park, NC: RTI International*.

Chen, B. 2007. "Cost of Food Security and Update of Cropping Mixes in China." Huazhong Agricultural University.

Chuwah, C., T. van Noije, D.P. van Vuuren, E. Stehfest, and W. Hazeleger. 2015. "Global impacts of surface ozone changes on crop yields and land use." *Atmospheric Environment* 106:11-23.

Emberson, L., P. Büker, M. Ashmore, G. Mills, L. Jackson, M. Agrawal, M.

Atikuzzaman, S. Cinderby, M. Engardt, and C. Jamir. 2009. "A comparison of North American and Asian exposure–response data for ozone effects on crop yields." *Atmospheric Environment* 43:1945-1953.

Feng, J., and T. Zhang. 2012. "Estimates of the Elasticity of Rural Labor Supply." 10:69-82.

Fuhrer, J., and F. Booker. 2003. "Ecological issues related to ozone: agricultural issues." *Environment International* 29:141-154.

Gale, H.F. 2013. "Growth and Evolution in China's Agricultural Support Policies." *USDA-ERS Economic Research Report*.

González-Fernández, I., D. Bass, R. Muntifering, G. Mills, and J. Barnes. 2008. "Impacts of ozone pollution on productivity and forage quality of grass/clover swards." *Atmospheric Environment* 42:8755-8769.

Graveline, N., and P. Mérel. 2014. "Intensive and extensive margin adjustments to water scarcity in France's Cereal Belt." *European Review of Agricultural Economics*:jbt039.

Griffin, J.M. 1977. "Long-run production modeling with pseudo data: electric power generation." *The Bell Journal of Economics*:112-127.

Heck, W.W., W.W. Cure, J.O. Rawlings, L.J. Zaragoza, A.S. Heagle, H.E. Heggestad, R.J. Kohut, L.W. Kress, and P.J. Temple. 1984. "Assessing impacts of ozone on agricultural crops: II. crop yield functions and alternative exposure statistics." *Journal of the Air Pollution Control Association* 34:810-817.

Heck, W.W., O. Taylor, R. Adams, G. Bingham, J. Miller, E. Preston, and L. Weinstein. 1982. "Assessment of crop loss from ozone." *Journal of the Air Pollution Control Association* 32:353-361.

Howitt, R.E. 1995. "Positive mathematical programming." *American Journal of Agricultural Economics* 77:329-342.

Just, R.E., D.L. Hueth, and A. Schmitz. 2005. *The welfare economics of public policy: a practical approach to project and policy evaluation*: Edward Elgar Publishing.

Kopp, R.J., and A.J. Krupnick. 1987. "Agricultural policy and the benefits of ozone control." *American Journal of Agricultural Economics* 69:956-962.

Lobell, D.B., and S. Asseng. 2017. "Comparing estimates of climate change impacts from process-based and statistical crop models." *Environmental Research Letters* 12:015001.

Maddala, G., and R.B. Roberts. 1980. "Alternative functional forms and errors of pseudo data estimation." *The Review of Economics and statistics*:323-327.

Mauzerall, D.L., and X. Wang. 2001. "Protecting agricultural crops from the effects of tropospheric ozone exposure: reconciling science and standard setting in the United States, Europe, and Asia." *Annual Review of Energy and the Environment* 26:237-268.

McCarl, B.A., and T.H. Spreen. 1980. "Price endogenous mathematical programming as a tool for sector analysis." *American Journal of Agricultural Economics* 62:87-102.

Mérel, P., and S. Bucaram. 2010. "Exact calibration of programming models of agricultural supply against exogenous supply elasticities." *European Review of Agricultural Economics*:jbq024.

Mérel, P., F. Yi, J. Lee, and J. Six. 2014. "A regional bio-economic model of nitrogen use in cropping." *American Journal of Agricultural Economics* 96:67-91.

Mills, G., A. Buse, B. Gimeno, V. Bermejo, M. Holland, L. Emberson, and H. Pleijel. 2007. "A synthesis of AOT40-based response functions and critical levels of ozone for agricultural and horticultural crops." *Atmospheric Environment* 41:2630-2643.

Muller, N.Z., and R. Mendelsohn. 2007. "Measuring the damages of air pollution in the United States." *Journal of Environmental Economics and Management* 54:1-14.

O'Connor, D., F. Zhai, K. Aunan, T. Berntsen, and H. Vennemo. 2003. "Agricultural and Human Health Impacts of Climate Policy in China."

Preckel, P.V., and T.W. Hertel. 1988. "Approximating linear programs with summary functions: Pseudodata with an infinite sample." *American Journal of Agricultural Economics* 70:397-402.

Reilly, J., F. Tubiello, B. McCarl, D. Abler, R. Darwin, K. Fuglie, S. Hollinger, C. Izaurralde, S. Jagtap, and J. Jones. 2003. "US agriculture and climate change: new results." *Climatic change* 57:43-67.

Tai, A.P.K., M.V. Martin, and C.L. Heald. 2014. "Threat to future global food security from climate change and ozone air pollution." *Nature Climate Change* 4:817-821.

Tang, H., M. Takigawa, G. Liu, J. Zhu, and K. Kobayashi. 2013. "A projection of ozone - induced wheat production loss in China and India for the years 2000 and 2020 with exposure - based and flux - based approaches." *Global Change Biology* 19:2739-2752.

Uchida, E., S. Rozelle, and J. Xu (2009) "Conservation payments, liquidity constraints and off-farm labor: impact of the Grain for Green program on rural households in China." In *An Integrated Assessment of China's Ecological Restoration Programs.* Springer, pp. 131-157.

Van Dingenen, R., F.J. Dentener, F. Raes, M.C. Krol, L. Emberson, and J. Cofala. 2009. "The global impact of ozone on agricultural crop yields under current and future air quality legislation." *Atmospheric Environment* 43:604-618.

Wang, X., W. Manning, Z. Feng, and Y. Zhu. 2007. "Ground-level ozone in China: distribution and effects on crop yields." *Environmental Pollution* 147:394-400.

Westenbarger, D.A., and G.B. Frisvold. 1995. "Air pollution and farm-level crop yields: an empirical analysis of corn and soybeans." *Agricultural and Resource Economics Review* 24:156-165.

Zhang, Z. 2004. "A Solution to Improve the Profits of Agricultural Sector." *Science & Technology Review* 2:49-51.

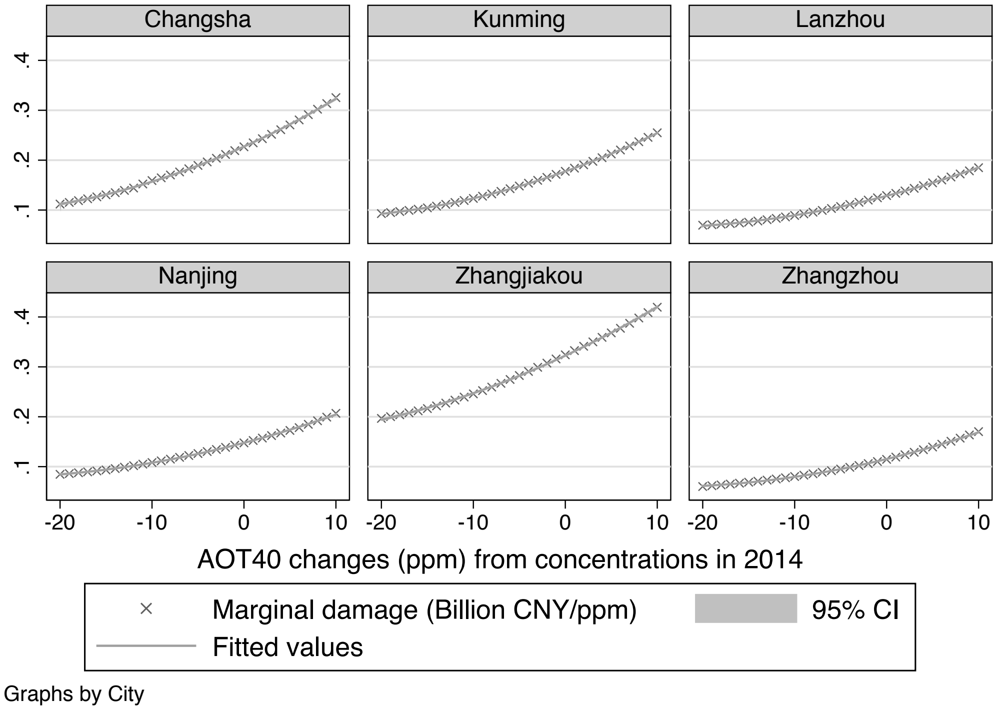

Figure 1. Select Ozone marginal damages summary functions

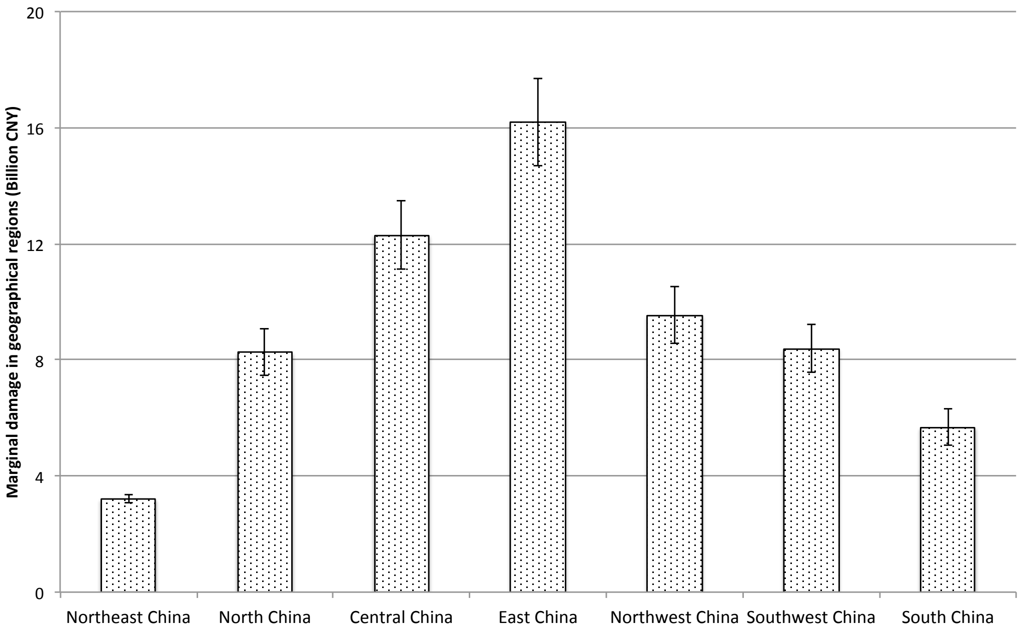

Figure 2. Agricultural marginal damage estimates arising from 2014 ozone concentrations for major Chinese regions

Table 1. Comparison between observed and CASM-generated prices and total land use or count of animals by commodity

Commodities	Production level in terms of planted area (1000 ha) / livestock numbers (1000 head)			Price (CNY/kg)		
	Observed	Model	% Deviation	Observed	Model	% Deviation
Rice	28826.2	29599.0	2.6	2.0	2.1	3.7
Wheat	26810.5	28132.4	4.7	1.6	1.7	3.0
Maize	41171.1	43035.3	4.3	1.6	1.7	3.6
Soybean	6216.9	6300.4	1.3	3.5	3.5	1.6
Peanut	4619.0	4563.6	-1.2	6.0	6.0	-0.7
Rapeseed	7632.3	7538.4	-1.2	3.5	3.5	-0.7
Cotton	4097.4	4216.6	2.8	10.6	10.9	2.7
Tobacco	1461.9	1506.0	2.9	15.3	15.9	3.6
Sugarcane	1756.5	1756.5	0.0	0.4	0.4	0.0
Sugarbeet	117.1	117.0	-0.1	0.4	0.4	0.1
Potato	9399.6	9543.1	1.5	0.9	0.9	1.5
Fiber crops	83.0	82.2	-0.9	6.8	7.0	2.2
Other grain crops	3019.5	3156.4	4.3	5.7	6.0	4.8
Vegetable and cucurbits	21842.5	21851.2	0.0	1.4	1.4	0.1
Other beans	1390.2	1354.1	-2.7	3.2	3.2	-0.6
Other oil crops	1556.6	1553.4	-0.2	6.0	6.0	0.0
Hen	16556.0	16535.5	-0.1	5.8	5.9	0.7
Broiler	120740.0	118852.8	-1.6	12.7	12.7	0.6
Cattle	47608.3	47425.5	-0.4	48.2	48.3	0.2
Cow	6587.3	6590.4	0.0	2.7	2.7	0.4
Hog	697894.7	698859.8	0.1	16.0	16.1	0.4
Sheep	270995.1	270119.9	-0.3	52.1	52.2	0.3

Notes:Livestock price information is for their main products, including eggs, chicken meat, beef, milk, pork and mutton of hen, broiler, cattle, cow, hog, and sheep. Other grain crops include oat, barley, and sorghum. Other beans include all dried beans, except soybean. Other oil crops include sunflower and sesame.

Table 2. Estimates of national total agricultural damages caused by 2014 ozone concentrations

Scenario	GAD		95% confidence interval			
	Estimate (Billion Yuan)	% of base	Lower bound† (Billion Yuan)	% of base	Upper bound (Billion Yuan)	% of base
Subregional marginal damage	1934.05	0.82	1629.77	0.69	2238.32	0.94
Provincial marginal damage	1558.98	0.66	1419.71	0.60	1698.25	0.72
Linear marginal damage	2165.06	0.91	-	-	-	-

Notes: † The lower bound and upper bound of the GAD is computed based on the 95% confidence intervals of the coefficients in quadratic form of Equation (4).

Table 3. Estimates of benefits of ozone concentration reductions

Ozone assumption	Total			Producers		Consumers	
	Total surplus change (Billion CNY)	% of base	Increase rates (%)	Producers' surplus change (Billion CNY)	% of base	Consumers' surplus change (Billion CNY)	% of base
-15%	358.71	0.15	-	-59.41	-0.05	418.12	0.33
-30%	678.21	0.29	89.07†	-112.83	-0.10	791.04	0.63
-45%	961.47	0.41	168.03	-136.15	-0.12	1097.62	0.87

Notes: †Increase rates are computed through dividing the amount of benefit increments from the first 15% ozone reduction by the gain at the first 15% ozone reduction.

Table 4. Provincial benefits or costs of ozone concentration reductions

Province	Ozone assumption					
	15% Reduction		30% Reduction		45% Reduction	
	Surplus (Billion CNY)	% of base	Surplus (Billion CNY)	% of base	Surplus (Billion CNY)	% of base
Anhui	10.66	0.10	20.48	0.19	29.60	0.27
Beijing	7.71	0.21	14.77	0.39	20.27	0.53
Chongqing	2.18	0.04	4.55	0.08	7.12	0.13
Fujian	6.93	0.10	13.77	0.20	19.61	0.29
Gansu	3.83	0.08	7.58	0.16	12.36	0.26
Guangdong	22.56	0.12	44.96	0.23	63.63	0.33
Guangxi	-3.24	-0.04	-5.12	-0.06	-5.95	-0.07
Guizhou	2.17	0.04	4.89	0.08	8.65	0.14
Hainan	-2.34	-0.15	-3.71	-0.23	-4.31	-0.26
Hebei	37.29	0.29	69.28	0.52	94.58	0.71
Heilongjiang	4.55	0.07	9.83	0.14	14.50	0.21
Henan	31.20	0.19	57.53	0.34	79.80	0.47
Hubei	10.31	0.10	19.79	0.19	28.55	0.27
Hunan	10.49	0.09	21.13	0.17	30.24	0.25
Jiangsu	27.01	0.19	51.27	0.36	70.88	0.50
Jiangxi	10.42	0.13	20.72	0.25	29.24	0.36
Jilin	8.75	0.18	17.20	0.35	24.38	0.49
Liaoning	15.95	0.21	30.69	0.39	42.52	0.54
Neimenggu	9.47	0.21	17.92	0.39	25.93	0.56
Ningxia	1.16	0.10	2.16	0.18	3.21	0.27
Qinghai	0.72	0.07	1.45	0.14	2.24	0.21
Shaanxi	4.41	0.07	6.21	0.09	9.14	0.13
Shandong	57.47	0.34	111.26	0.63	156.76	0.89
Shanghai	7.11	0.17	13.70	0.32	18.89	0.44
Shanxi	11.35	0.18	21.45	0.33	30.06	0.46
Sichuan	11.18	0.08	22.09	0.15	32.79	0.22
Tianjin	5.90	0.22	11.15	0.41	15.25	0.56
Tibet	0.96	0.17	1.87	0.33	2.60	0.46
Xinjiang	19.67	0.49	37.03	0.90	52.07	1.27
Yunnan	1.45	0.02	4.44	0.05	8.36	0.10
Zhejiang	14.52	0.15	27.88	0.28	38.50	0.39

Table 5. Effects of ozone concentration reductions on grain production

Ozone assumption	Grain supply (Million ton)	% of base	Rice (Million ton)	% of base	Wheat (Million ton)	% of base	Maize (Million ton)	% of base
-15%	29.57	5.39	-0.50	-0.24	25.16	19.94	4.91	2.28
-30%	57.63	10.51	0.26	0.13	48.44	38.39	8.93	4.14
-45%	91.83	16.75	0.97	0.47	78.86	62.50	12.00	5.56

Table 6. Effects of ozone concentration reductions on provincial grain production

Province	Base (Million ton)	Ozone assumption					
		15% Reduction		30% Reduction		45% Reduction	
		Output (Million ton)	% Change	Output (Million ton)	% Change	Output (Million ton)	% Change
Anhui	32.07	1.82	5.66	3.12	9.72	4.96	15.47
Beijing	0.62	0.06	10.17	0.14	21.99	0.22	36.01
Chongqing	7.84	-0.03	-0.38	0.00	-0.06	0.06	0.82
Fujian	5.11	0.11	2.10	0.20	3.88	0.29	5.60
Gansu	8.73	1.31	15.00	2.69	30.83	4.26	48.79
Guangdong	11.52	-0.21	-1.84	-0.33	-2.86	-0.43	-3.71
Guangxi	14.12	-0.26	-1.86	-0.32	-2.24	-0.33	-2.36
Guizhou	8.03	0.19	2.34	0.23	2.91	0.36	4.52
Hainan	1.53	-0.08	-5.46	-0.15	-10.10	-0.22	-14.39
Hebei	31.72	3.32	10.47	6.31	19.89	9.67	30.48
Heilongjiang	55.73	0.19	0.35	0.39	0.70	0.60	1.08
Henan	55.13	6.30	11.42	11.08	20.10	16.81	30.49
Hubei	24.14	0.92	3.81	1.69	6.98	2.56	10.60
Hunan	27.93	0.12	0.44	0.06	0.23	0.05	0.17
Jiangsu	33.31	2.60	7.81	5.89	17.69	9.97	29.93
Jiangxi	20.08	-0.13	-0.63	0.03	0.14	0.19	0.97
Jilin	33.65	0.35	1.05	0.66	1.97	0.99	2.95
Liaoning	16.47	0.11	0.64	0.27	1.63	0.45	2.70
Neimenggu	24.52	1.37	5.57	2.41	9.82	3.72	15.15
Ningxia	3.27	0.23	6.92	0.43	13.23	0.72	21.93
Qinghai	0.62	0.02	3.91	0.01	0.83	0.03	4.31
Shaanxi	10.62	1.67	15.70	4.27	40.21	7.45	70.17
Shandong	42.90	4.49	10.47	9.53	22.21	15.74	36.70
Shanghai	1.09	0.09	8.39	0.19	17.46	0.30	27.93
Shanxi	12.40	1.47	11.84	2.54	20.51	3.73	30.12
Sichuan	27.39	0.66	2.41	0.88	3.23	1.43	5.23
Tianjin	1.71	0.31	18.28	0.62	36.45	0.99	57.59
Tibet	0.94	0.00	0.01	0.00	0.05	0.00	0.10
Xinjiang	13.47	1.31	9.71	2.28	16.96	3.41	25.29
Yunnan	15.10	0.90	5.99	1.77	11.74	2.70	17.86
Zhejiang	6.53	0.37	5.62	0.74	11.29	1.15	17.65

Table 7. Potential emission charges of surface ozone precursor

	Ozone precursor emission charge†			
	Lower bound		Upper bound	
	VOC charge (CNY/kg)	NO_X charge (CNY/kg)	VOC charge (CNY/kg)	NO_X charge (CNY/kg)
	1.26	1.26	40	10
Aggregate emmission charge (CNY Billion)	57.58		1204.51	
% of aggregate damage	3.31		69.25	

Notes: †NO_X emission is collected from industry in 2014, and VOC emission is the aggregate level from industry in 2012 due to data availability.

Appendix A： CASM Model Structure

CASM is a multiple-region, multiple-commodity, price-endogenous, partial equilibrium, mathematical programming model designed to simulate the effects of demand, policy, technological, and environmental changes on agricultural land use, crop mix, production, market prices, imports, exports, and consumers' and producers' surplus, as described in McCarl and Spreen (1980). In CASM, China is divided into 365 subregions (areas around prefecture-level cities) to reflect both the heterogeneous production and resource characteristics of each agricultural area. Each subregion possesses endowments of arable land and labor along with varying cropping and livestock mixes with different production budgets.

We model China's regional crop and livestock production as if it results from the rational maximization of aggregate consumers' and producers' surplus subject to limited resource constraints as well as demand and supply balances. The technology is represented by crop- and livestock-specific linear production functions in the form of alternative production budgets. The agricultural production possibilities for crop and livestock production, are denoted as i; subscript r and r' represent subregions; j represents inputs used for commodity production and k nutrients derived from farm family consumption of farm produced products. The regional economic optimization model for China's agricultural sector is defined as follows[3]:

$$\begin{aligned}\text{Max} \sum_i \int P_i^D(QA_i)\mathrm{d}QA_i - \sum_j \int P_j^S\left(X_j^M\right)\mathrm{d}X_j^M - \sum_i \int P_i^{IM}(QA_i^{IM})\mathrm{d}QA_i^{IM} \\ + \sum_i \int P_i^{EX}(QA_i^{EX})\mathrm{d}QA_i^{EX} - \sum_r \int P_r^L(L_r^M)\mathrm{d}L_r^M - \sum_r \sum_i \sum_t C_{ri}^{ST} Q_{rit}^{ST} \\ - \sum_i \sum_t CT_i^{ST} QT_{it}^{ST} - \sum_r \sum_{r'} \sum_i \sum_t CM_i QM_{(r,r')it} \qquad \text{(A1)}\end{aligned}$$

[3] The full model is written using GAMS, and a full list of the equations is available upon request.

$$
\text{s.t.}\begin{cases}
CS_{it}QA_i + \sum_r \sum_{r'} QM_{(r',r)it} + Q_{it}^{EX} + QT_{it}^{ST} \leq \sum_r \sum_{r'} QM_{(r,r')it} + Q_{it}^{IM} + QT_{it-1}^{ST} \forall r,i,t & \text{(A2)} \\
Q_{rit}^{SELF} + \sum_{r'} QM_{(r,r')it} + Q_{rit}^{ST} \leq Y_{rit}AP_{ri} + \sum_{r'} QM_{(r',r)it} + Q_{rit-1}^{ST} \forall r,i,t & \text{(A3)} \\
\sum_i RU_{rij}AP_{ri} \leq \bar{X}_{rj} \forall r,i,j & \text{(A4)} \\
\sum_i LU_{ri}AP_{ri} \leq L_r^F + L_r^M \forall r,i & \text{(A5)} \\
N_{rk} \leq \sum_i a_{ik}Q_{rit}^{SELF} \forall r,i,k,t & \text{(A6)} \\
\sum_t Q_{it}^{EX} = QA_i^{EX} \forall i,t & \text{(A7)} \\
\sum_t Q_{it}^{IM} = QA_i^{IM} \forall i,t & \text{(A8)}
\end{cases}
$$

The model maximizes consumers' and producers' surplus in Equation (A1) subject to market supply-demand balances, resource and family nutritional constraints. This model simulates cost-minimizing consumers and profit-maximizing producers, as discussed in McCarl and Spreen (1980). Samuelson (1952, p.288) stated that "the objective function is artificial in the sense that no competitor in the market will be aware of or concerned with it." The first-order condition characterizes an economic equilibrium and thus depicts the government as an "Invisible Hand" that sets the subsidy and alters the farmers' optimal choice. Thus, the solution of this programming model can be characterized as a simulation of agricultural sector behavior under the assumption of perfect competition.

In principle, we allow all commodities and farm labor to have endogenous market prices as China is a key player in the world market and a net importer in most major agricultural products (Gale, 2013), we assume that the import prices of agricultural commodities increase when China increases the quantity of imports.

As Uchida, et al. (2009) pointed out that China's labor market is incomplete, most of the farm labor comes from family sources, and they occasionally hire labor during planting and harvest seasons. Thus, we include a regional labor supply curve that first supplies labor from the available family pool then allows hired labor once the usage exceeds available family labor.

In addition, consumption is set up on a monthly basis with the family satisfying its nutritional needs then market consumption. Monthly storage is also incorporated in the model. Thus, the cost of storage is included in the objective function.

Table A1. Definitions of terms

Variables	Definitions
QA_i	Annual country-wide, total, non-farm, domestic demand for commodity i that is bought from market
Q_{rit}^{SELF}	Amount of commodity i that is used at the farm level from the farmers' own production being either consumed by the farm family or farm livestock in region r in period t
CS_{it}	Share of non-farm consumption for commodity i that occurs in period t
QA_i^{EX}	Amount of commodity i exported annually
Q_{it}^{EX}	Amount of commodity i exported in period t
QA_i^{IM}	Amount of commodity i imported annually
Q_{it}^{IM}	Amount of commodity i imported in period t
Q_{rit}^{ST}	Amount of commodity i stored by farmers in region r in period t
QT_{it}^{ST}	Amount of commodity i stored in market in period t
$QM_{(r,r')it}$	Amount of commodity i moved out from region r to region r' in period t
$P_i^D(QA_i)$	Inverse non-farm demand function for commodity i
$P_j^S(X_j^M)$	Inverse supply function for purchased factor j
$P_i^{IM}(QA_i^{IM})$	Inverse supply function for imports of commodity i
$P_i^{EX}(QA_i^{EX})$	Inverse demand function for exports of commodity i
L_r^M	Amount of hired labor supplied in region r
$P_r^L(L_r^M)$	Inverse supply function for hired labor in region r
X_j^M	Quantity of purchased factor j
AP_{ri}	The level of production activity i in region r, such as planted area of a crop or number of heads of a type of livestock
RU_{rij}	Amount of input j used for the production of commodity i in region r
LU_{ri}	Amount of labor used to produce one unit of production item i in region r

Parameters	Definitions
Y_{rit}	Yield of production activity i in region r in period t
C_{ri}^{ST}	Unit cost of storage by farmers for commodity i in region r
CT_i^{ST}	Unit cost of storage for commodity i in market
CM_i	Unit cost of transportation for commodity i
$\bar{X}_{rj}$	Endowed amount of input j in region r, such as land, family, and labor
L_r^F	Amount of family labor supply in region r
N_{rk}	Minimum requirement of nutrient k in region r arising from on-farm consumption for human beings and livestock in a period
a_{ik}	Content of nutrient k in commodity i

Equation (A2) presents the aggregate demand-and-supply balance for China's domestic agricultural commodity market by period. The equation shows that the demand of a specific commodity includes domestic consumption, commodities transported out to regional markets, exports, and storage into the next period. Supply comes from commodities transported in from production regions, imports, and storage from the last period. Demand is less than or equal to the total supply. As agricultural production and consumption occur over time, the market-clearing conditions are represented for each month. To simplify the model, the monthly share of non-farm consumption CS_{it} is set as 1/12 the annual estimate.

Equation (A3) shows the regional demand-and-supply balance by period. The demand includes farmers' self-consumption, amount of a commodity transported from each region r to other regions, and storage into the next period. Local supply is from production, commodities transported in from other regions to this region r, and storage from the last period.

Equation (A4) is a resource-endowment constraint for each subregion, restricting the use of land and family labor in agricultural production to be less than or equal to the total available land and family labor endowment, respectively. On rice production, a regional land suitable for maximum paddy land available is added to restrain rice to only flat lands with water access.

Inequality (A5) states that the total amount of labor used in agricultural production should be less than or equal to the aggregate amount available from the two sources of labor, namely, family labor and hired labor from the market.

This inequality is a market-clearing condition that is similar to Constraint (2) but only for labor.

Constraint (A6) captures the nutrition requirements for the family and livestock on a regional, monthly, and nutrient basis. For farm families, we assume that 60% of calories and protein comes from on-farm grain consumption. In the average Chinese diet about 65% of the calories come from rice. For crops fed to livestock, multi-commodity diet alternatives are entered for each different animal types, and the model chooses the optimum. Generally, maize and soybeans are the most important feeds for livestock.

Equations (A7) and (A8) require the aggregates of monthly imports and exports to be equal to the annual values of trade.

Appendix B: Ozone Concentration Measures

Different ozone exposure metrics are defined as:

$$M7\ or\ M12 = \frac{1}{n}\sum_{i=1}^{n} O_3^i$$

$$AOT40 = \sum_{i=1}^{n}\left(O_3^i - 40\right) \quad \text{for} \geq 40 \text{ ppb}$$

$$SUM06 = \sum_{i=1}^{n}(O_3^i - 60) \quad \text{for} \geq 60 \text{ ppb}$$

$$W126 = \sum_{i=1}^{n}\frac{1}{1 + 4403e^{-126O_3^i}} \cdot O_3^i$$

where O_3^i is the hourly mean ozone concentration in ppb, and n is the number of hours during growing season. $M7$ and $M12$ are measured during daylight hours, 9:00 to 16:00 and 8:00 to 20:00, respectively. *AOT40* is defined as the cumulative hourly ozone volume mixing ratio above a threshold of 40 ppb during daylight (8:00–20:00) in three months of growing seasons when radiation $\geq 50\ \text{Wm}^{-1}$ (Aunan, et al., 2000, Chuwah, et al., 2015). In the $W126$ estimation, w_i is a weighting function assigning greater weight to higher levels of hourly ozone with an inflection point at 65 ppb (Tai, et al., 2014).

Appendix C: Dose Response Functions

Relative yield is defined as $RY(O_3) = Y/Y_0$, where Y is the realized yield, and Y_0 is the maximum potential yield without ozone impacts. Although Mills, et al. (2007) provided numerous crop-response functions based on meta-analysis, AOT40-based dose-response functions normally have an intercept, which is generally different from 1. We use the same method as that of Van Dingenen, et al. (2009) to rescale those functions to ensure that the intercept of RY is equal to 1 when $AOT40 = 0$. Crop-exposure response functions are defined in Table C1 as follows.

Table C1. Dose-response functions used to estimate relative yields of crops based on AOT40

Crops	Dose-response functions[a]	References
Rice	RY=1-0.00415AOT40	Mills, Buse et al., 2007
Wheat	RY=1-0.01626AOT40	Mills, Buse et al., 2007
Maize	RY=1-0.00353AOT40	Mills, Buse et al., 2007
Soybean	RY=1-0.01137AOT40	Mills, Buse et al., 2007
Peanut[b]	RY=1-0.01495AOT40	Mills, Buse et al., 2007; O'Connor, Zhai *et al*., 2003
Rapeseed	RY=1-0.00622AOT40	Mills, Buse et al., 2007
Cotton	RY=1-0.01495AOT40	Mills, Buse et al., 2007
Tobacco	RY=1-0.00529AOT40	Mills, Buse et al., 2007
Sugarcane[b]	RY=1-0.01495AOT40	Mills, Buse et al., 2007; González-Fernández *et al.,* 2008
Sugarbeet	RY=1+0.0058AOT40	Mills, Buse et al., 2007
Potato	RY=1-0.00576AOT40	Mills, Buse et al., 2007
Fiber crops[c]	RY=1+0.0027AOT40	Mills, Buse et al., 2007
Other grain crops[d]	RY=1+0.00063AOT40	Mills, Buse et al., 2007
Vegetable and cucurbits[e]	RY=1-0.01107AOT40	Mills, Buse et al., 2007
Other beans[f]	RY=1-0.01719AOT40	Mills, Buse et al., 2007
Other oilcrops[g]	RY=1-0.01137AOT40	Mills, Buse et al., 2007; Chuwah, van Noije *et al*., 2015

Notes: The unit of AOT40 is ppm.
a:We rescale functions based on the method suggested by Van Dingenen, Dentener *et al*. (2009).
b:Use the dose-response function of cotton.
c:Use the dose-response function of broccoli.
d:Use the dose-response function of barley.
e:Use the average dose-response functions of tomato, turnip, onion and lettuce.
f:Use the dose-response function of pulses.
g:Use the dose-response function of soybean.

Few studies in China have been conducted for crop sensitivities to ozone exposure. Considering that Asian crops are known to be more sensitive to ozone exposure than North American crops (Aunan, et al., 2000, Emberson, et al., 2009), the utilization of dose-response functions derived from Europe and North America will likely provide conservative estimates of ozone effects (Chuwah, et al., 2015).