Supplemental Information: 2018 FASOMGHG Overview and Model Development Documentation

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 The Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG) is a dynamic nonlinear programming model of the U.S. forest and agriculture sectors. The model simulates land allocation between competing activities in the forest and agricultural sectors over a finite time horizon and projects the resulting market and environmental impacts. The model maximizes the net present value of the sum of consumer and producer surplus in the two sectors, subject to constraints including consistency with biophysical parameters, technical input-output relationships, market clearing conditions, and total land availability. Previous studies have used FASOMGHG to examine potential impacts of GHG mitigation policies, climate change impacts, bioenergy production, timber harvest policies, and a variety of other scenarios that influence land allocation and production markets within the forest and agricultural sectors.

 We recently developed a new 2018 version of the FASOMGHG model, which offers several key improvements relative to previous versions (Table 1). The forest sector model has been completely redesigned and is now based on supply- and demand-side aggregations of the Land Use and Resource Allocation (LURA) model described in Latta et al. (2018). Furthermore, we incorporated land conversion and logging residual marginal cost curves for each region in place of using average regional values, replaced the previous representation of international trade with a gravity model to project forest product trade flows between the U.S. and trade partners, restructured the forest commodity representation and regional processing capacities, and updated GHG accounting procedures for aboveground forest biomass carbon.

12 **Table 1. Areas with Data and Structural Model Updates**

1 1. Model Summary

 FASOMGHG represents land competition between forestry, crop production, and livestock production (pasture and crop-land pasture for grazing) within an intertemporal optimization framework. FASOMGHG provides a more complete assessment of the full market impacts or opportunity costs of policy constraint relative to approaches that focus on a single sector, explore only direct impacts, and/or explore a smaller subset of commodities and land uses. FASOMGHG can project impacts resulting from landowner behavioral responses because it offers broad coverage of forestry and agricultural commodities and production possibilities. Such land use behavior in the model includes changes in the agricultural production area, crop switching, movements between alternative uses, and other intensive margin responses (e.g., switching between irrigated and dryland crop production or plantation forestry). FASOMGHG also models interactions between crop and livestock markets through effects on feed, land, and other markets. Finally, the model includes detailed GHG accounting that captures carbon fluxes from the majority of activities in these sectors.

 FASOMGHG incorporates agricultural activities across the conterminous United States, broken into 63 agricultural production regions and 11 forest and market regions. The model is typically run over 60 to 100 years on a 5-year time step. Model solutions reflect simultaneous multi- period, multi-commodity, multi-factor market equilibria, and model results provide a dynamic simulation of prices, production practices, output, consumption, net GHG emissions, and a variety of other environmental and economic measures within these sectors. Key endogenous variables in FASOMGHG include:

• production and consumption;

• export and import quantities or net trade;

Several of these individual updates are discussed in detail below.

2.1 Spatial Aggregation

2 To integrate the LURA modeling system into FASOMGHG we aggregated the plot level data into 11 regions based on forest type, stand age (in decadal increments), management intensity, owner, and productivity class (Figure 1). Specifically, forest types were aggregated to the FASOM region level to maintain a consistent national forest inventory and age-class distribution with the 2015 starting period in LURA. Yield growth curves assigned to different forest type, region, and site class were based on a spatially weighted average across Eco Provinces overlaying FASOM regions. New forest types, site classes, and ownership classes included in the model are shown in Table 0-1. Furthermore, we similarly aggregated capacities from individual processing centers to generate

estimates of regional processing capacity in FASOMGHG and a consistent national demand

level for individual forest products to align with LURA.

Figure 1. Map of the 11 2018 FASOMGHG Regions

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1 **Table 0-1 Unique Forest Identifiers**

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4 2.2 Forest Sector Commodity Categories

 The updated forestry sector model relies on a simplified product market structure, which no longer differentiates between privately and publicly supplied log products but includes greater detail on byproducts. The new commodity categories are presented in Table 3, including timber harvest, log harvest, and byproducts. The model assigned harvested timber to one of four log categories, which can be used to meet exogenous export demand or be processed to create secondary products.

 In the FASOMGHG framework, primary commodities can be used directly or converted to secondary products via processing activities. For example, the paper could be made from pulp logs or from logging residues. Secondary products are based on categories used by the USDA Forest Service to measure U.S. forest sector production (Table 4). The original model used 40 product categories based on the FAO classification; the updated model includes a simplified classification system of 16 secondary products and is consistent with the USDA classification system. The updated version also uses spatially explicit mill capacity and production schedules

- to estimates regional processing costs of harvested logs across nine U.S. production regions and
- Canada (see Latta, Baker et al. (2018) for further explanation on processing budgets).

1 **Table 4. New Secondary (Processed) Commodities**

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3 2.3 GHG Accounting

 We model the following carbon pools: down deadwood; standing deadwood; understory; litter; live tree aboveground; live tree belowground; and forest soils. We calculate the change in woody biomass pools using flux values based on forest type, management intensity, productivity class, and age class. The approach is consistent with carbon accounting methods in Latta, Baker et al. (2018) but aggregated to the eleven study regions using the spatial aggregation procedures described previously.

 FASOM-GHG tracks soil carbon in agricultural land uses, forests, and soil carbon. On the forestry side, the approach used is adapted from Birdsey (1996), which assumed constant soil 3 carbon values on forests for all except the South³, and Smith et al. (2006) , which has all carbon in forest soils assumed to be constant over time, with variation across region and forest type. We base initial soil carbon values for forests forest on an approximation of the values and trends presented in Birdsey et al. (1996) and Smith et al. (2006). Agricultural soil carbon values (for pasture and cropland uses) are based on outputs from the biogeochemical model Century, as described in Beach et al. (2010). Century meta-data is used to evaluate the difference in stable soil carton stock values across regions, crops, and between tillage methods (conventional, conservation, and zero till). We assume a saturation period for tillage over multiple decades to reach a new stock level per unit area, and this saturation trend and new stock level varies by region (as described in Beach et al. [2010]).

 We also consider soil carbon sequestration resulting from land use change. For example, when land converts from agricultural use to forests via afforestation, there is a period of soil adjustment from the prior land use fixed soil amount to the new land use fixed soil amount. More information on soil carbon adjustments due to endogenous land use changes, including tables with all regional parameters used (including initial carbon stocks by land use type), can be found in a supplemental appendix of the EPA (2014) report *Framework for Assessing Biogenic CO2 Emissions from Stationary Sources*.

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³ Birdsey (1996) had minor variation (<10%) in soil carbon for southern forest over the life of a stand

 Carbon stored in harvested forest products is not accounted for in the 2018 version of FASOMGHG, though previous studies have shown the net flux from these pools to be relatively small (Tian et al. 2018).

2.4 Land Use Change (LUC) Supply Curves

 The FASOMGHG model endogenously allocates land to either forestry or agriculture based on maximizing the net present value of the future stream of the sum of consumer and producer surplus. In previous iterations, the model relied on the average cost of land conversion from cropland, cropland pasture, and pasture to forestry, ignoring the heterogeneous nature of pasture, cropland, and cropland pasture quality. To better account for the varying cost associated with land conversion, we incorporated marginal cost curves of land moving into forestry within FASOMGHG. To create supply curves for individual land types moving into forestry, we developed non-parametric step functions to represent the marginal cost of land conversion using county-level afforestation costs estimated from Nielsen, Plantinga et al. (2014) to create regional afforestation supply curves for agriculture, pasture, and rangeland. These supply curves were incorporated into the 2018 version of FASOMGHG dynamically such that afforestation costs increase over time based on net afforestation amounts from previous periods. Additional discussion of these methods and an illustrative comparison to alternative afforestation cost specifications is available in Cai et al. (2018).

2.5 International Forest Product Trade

 Import and export levels and growth rates for forest products are exogenous and align with a previously developed gravity model of forest product trade from Larson et al. (2018). We projected forest product import and export demand growth as a function of the impact of importer GDP, exporter GDP, and the distance between countries on exports using Poisson

 pseudo-maximum likelihood techniques. The econometric model was estimated based on trade data for thirteen product categories between country pairs from the Food and Agriculture Organization of the United Nations, from 1997 to 2014. Using the estimated elasticities, in 4 combination with estimates of future GDP from the AEO 2017 Reference Case (for the U.S.) and 5 Shared Socio-economic Pathways for other regions (Riahi et al., 2017), we project future U.S. exports and imports to the year 2050 for each forest item category. Trade flows are held constant for all product categories after 2050.

3. Agriculture Sector

3.1. Crop Mix

 The FASOMGHG model allows for transitions among alternative crop types within a region, with regional crop mix constraints that limit movement of specific crop groups according to the historically observed minimum and maximum area bounds since 1980. The 2018 FASOMGHG updates these historical minima and maxima to account for recent trends to 2009 – 2015 using data from USDA's National Agricultural Statistics Service (NASS) for the crops listed in Table 5. We obtained crop data at the state level and at the county level for the six states which are represented by multiple sub-regions and aggregate the data to each of the FASOMGGHG 63 agricultural sector regions.

Table 5. List of Crops Selected for Updating

 FASOMGHG uses information on acres harvested from both irrigated land and dryland, which are pulled from the USDA-NASS database at the state and county level for all available commodities. In these cases where data are not available, we calculated missing values based on the reported acreages in combination with historical FASOMGHG proportions from 2000 – 2008 between land types. For a handful of fruit and vegetable commodities, NASS provides total acres harvested but does not break this value down by irrigation status or fresh/processed category. Therefore, we estimated these proportions using historical FASOMGHG data. In addition, the NASS includes eight types of wheat, while FASOMGHG includes five types (Table 6). To map the NASS wheat types to FASOMGHG wheat types we multiplied the total area of wheat harvested from NASS by the relative proportions of the total wheat area from the existing FASOMGHG data.

12 **Table 6. NASS vs. FASOMGHG Wheat Types**

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 Certain data collected at the county-level from NASS was often aggregated to a combined county district or withheld, to preserve landowner privacy. We discovered that this largely impacted two crops, peas and hay, in the years 2013 and 2014. However, these omissions were limited, and we did not observe that the omission of data decreased the total reported acreage for

these crops in these years relative to other years (Figure 2). As a result, we did not correct for these

omissions in the model.

Figure 2. Total U.S. Harvested Acres for Peas and Hay 2011 - 2015

3.2 Agricultural Commodity Trade

 We updated trade prices for key commodities (Table 7) using data from the Food and Agricultural Organization of the United Nations (FAO) FAOSTAT database and several other data sources, using appropriate unit conversion where necessary (Table 8). In rare cases where new data was not available, we retained the previous price and quantity data and elasticity parameters. In cases where data was not sufficiently disaggregated, we used historical proportions from the previous FASOMGHG version to add product differentiation. To verify the quality and compatibility of the new data across all sources, we calculated the percent differences between old and new commodity data and did not observe substantial differences.

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3 **Table 8. International Agricultural Trade Data Sources**

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 An important update to the mitigation technologies represented in the model is the inclusion of winter cover cropping activities. We determined the cost of implementing winter cover crops using data from the USDA's Natural Resources Conservation Service (NRCS) (2014) and from a number of other data sources (Table 9). We used the USDA NRCS (2014) data to determine the cost per acre of various combinations of tillage (i.e. till or no-till), seeds (e.g. legumes, grains, or a mix), and termination method (i.e. herbicide or tilling – assumed to be mutually exclusive). Then, we constructed a simple cost model from this data, both for a corn cash crop and a soybean cash crop. We calculated relative costs of grain and legume seeds compared to the base case (a mix of the two types) using per acre costs from Clark (2008), resulting in the following relative cost multipliers:

- 14 grain-legume mix: 1
- legume: 1.229
- grain: 0.771

The USDA NRCS (2014) provides implementation cost data as a combination of labor and fuel

costs. For simplicity, we assumed that these costs split evenly into labor and fuel costs.

Similarly, we assumed the termination costs were split into labor, fuel, and herbicide costs, with

herbicide costs only included for no-till acres. Tables 10 and 11 illustrate the mitigation cost

structures assumed for each variation of the cover cropping measure.

2 **Table 9. Data Sources Reviewed for the Cover Crop Mitigation**

- 3 Note: Full references provided at the end of this memo.
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5 *Table 10. Cover Cropping – Corn with Tillage and without Tillage (\$/Acre)*

2 **Table 11. Cover Cropping – Soy with Tillage and without Tillage (\$/Acre)**

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4 We obtained data on total existing cover crop acres by U.S. state from the 2012 USDA

5 Agricultural Census. To account for existing adoption of cover cropping, we set the existing

6 cover crop acreage as a region-specific lower bound. This constraint is applicable to regions

7 where cover cropping is permitted in the model, which is determined by whether it was hosts

8 land for corn and/or soybeans with winter climate conducive for winter cropping. Based on Lal

9 et al. (1998), we identified 33 FASOMGHG sub-regions that met this requirement (Table 12).

10 **Table 12. List of FASOMGHG 63 Regions Eligible for Cover Cropping**

 To add cover crop options to the FASOMGHG framework, we expanded the crop technology dimension within each of the pre-existing soybean and corn production schemes. We created crop budgets for the four cover crop technologies (i.e. corn and soy with and without tillage) by duplicating their baseline budgets for each region, crop, tillage practice, and fertilizer type, and then applying cover crop-specific percentage adjustments to specific input categories to reflect differences in costs and resource usage relative to baseline production. This allowed for existing constraints that had already affected crop-specific production (ie. land, resource, crop- mix) to remain applicable as any parameters subject to such production constraints were first summed over the crop technology dimension. We adjusted the agricultural fuel-use GHG account for carbon to reflect the increased agricultural fuel requirements, equal in proportion to the adjustment in diesel and gasoline input use.

 To account for the GHG impacts of cover crops, we collected data from two national studies, Lal et al. (1998) and Sperow et al. (2003), which provided annual per hectare estimates of soil carbon sequestration from cover crops. We averaged these estimates, resulting in a national average soil carbon sequestration rate of 0.3145 tCO2e/acre. We assumed that the implementation of cover cropping has no impact on yields, as there is no consensus in the literature on the magnitude of the yield impacts (IDALS et al. (2013), USDA NRCS (2014), Carlson and Anderson 2013, Miguez and Bollero (2005), Tonitto et al. (2006)).

1 **Table 13. Cost Factor Sources for Manure Management Costs**

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 Labor and materials factors were constructed using the Commodity Costs and Returns reports from USDA's Economic Research Service (USDA, 2018) for the specific crops and livestock types included in the model. Data were available at the USDA Farm Resource Region level. These data were mapped to states using a county-to-Resource Region mapping from USDA. Materials cost indices were constructed using components of operating costs detailed in 8 the commodity costs and returns report that were not already accounted for in the model (e.g., custom operations, repairs, irrigation, or other variable expenses) relative to U.S. values. Relative costs of inputs like seeds, fertilizer, fuel, or chemicals were not included in these materials cost

 indices because the model already accounts for them. The term "materials" is intended to capture 2 all the nonlabor and nonenergy recurring O&M costs or potential savings associated with each mitigation measure.

 Labor cost indices were calculated using regional hired labor costs as reported in the USDA Commodity Costs and Returns report relative to U.S. values. These relative costs were allocated to states using an average weighted by the area of the state in each Resource Region.

 We next obtained GHG emissions factor data from EPA's 2016 U.S. GHG Inventory. 8 Additionally, the following equation was adapted from the IPCC (2006) guidelines to calculate state-by-state emission factors by livestock type *T*:

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$$
E F_{(T)} = V S_{(T)} \times [B_{o(T)} \times 0.67 kg/m^3 \times \sum_{s} \frac{MCF_s}{100} \times MS_{(T,s)}]
$$

Where:

VS: Constants for volatile solid production

(*Bo*): Maximum methane producing capacity for manure

(MCF): Methane conversion factors

(MS): Fraction of manure handled by specific waste management systems which are

16 taken from the EPA's 2016 U.S. GHG Inventory.

We calculated emissions from manure management for swine and dairy cattle separately.

For four of the five categories of swine presented in the GHG Inventory, we calculated a

weighted average emission factor for each state using the state-by-state population of each

category of swine. The fifth category, market swine, are not represented at the state level, so we

assume that the national distribution of market swine across its four weight classes apply to each

 state. We re-calculated all population data from USDA NASS, using 2014 data to correspond with the 2014 emissions data we used previously. We calculated a national average emission factor from these state-by-state average pig emission factors, using state-level swine population as a weight. For dairy cattle, we calculated a national weighted average emission factor using the existing emission factors and state-level dairy cattle population as a weight. We then calculated state adjustment factors by dividing state emissions factors for both dairy cattle and pigs by their respective national average emission factors.

3.4.2 Enteric fermentation

 We calculated emission factors for enteric fermentation for dairy and beef cattle using the following equations, taken from the EPA 2016 U.S. GHG Inventory Annex 3:

$$
VS = [(GE - DE) + (UE \times GE)] \times \frac{(1 - ASH)}{18.45}
$$

Where:

$$
DayEnt = \frac{(GE \times Y_m)}{55.65}
$$

- Where:
- (*GE*): Gross energy
- (*DayEmit*): daily emissions
- (*Ym*): yearly emission factors are calculated on a state-by-state basis using the equations above.
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Emission factor = $DayEmit \times 365.25$

 Total emissions were divided by yearly state-level emissions factors calculated above per head and by animal type (U.S. GHG Inventory 2016). We checked these new estimates against USDA NASS data for categories with state-level coverage as well as total populations. From the yearly emission factors, we calculated weighted averages on a state by state basis of dairy cattle and beef cattle. We then calculated a national weighted average for dairy cattle and beef cattle, using animal population as a weight. Using the state and national weighted average emission factors for dairy and beef cattle, and an adjustment factor for each state and category of cattle (dairy or beef), by dividing the respective state emission factor by the respective national emission factor.

 We developed region-specific marginal abatement cost curves with 125 incremental price steps to represent cost and mitigation reduction in each region for the periods 2015, 2020, 2025 and 2030. These non-parametric step functions were incorporated into FASOMGHG using separable programming procedures. Figures 3 and 4 below show the MAC curves for manure management and enteric fermentation respectively. Mitigation costs and abatement potential are held constant after 2030.

Figure 3. Regional MAC Curves for Manure Management - 2030

Figure 4. Regional MAC Curves for Enteric Fermentation – 2030

4. Conclusions

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