Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

Enhanced representation of soil NO emissions in the Community Multi-scale Air Quality (CMAQ) model

Quazi Z. Rasool[1], Rui Zhang[1], Benjamin Lash[1*], Daniel S. Cohan[1], Ellen Cooter[2], Jesse Bash[2] and Lok N. Lamsal[3,4]

[1]{Department of Civil and Environmental Engineering, Rice University, Houston, Texas, USA}

[2]{Computational Exposure Division, National Exposure Research Laboratory, Office of Research and Development, US Environmental Protection Agency, RTP, NC, USA}

[3]{Goddard Earth Sciences Technology and Research, Universities Space Research Association, Columbia, MD 21046, USA }

[4]{NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA}

[*]{now at: School of Natural Sciences, University of California, Merced, CA}

Correspondence to: Daniel Cohan (cohan@rice.edu)

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

Abstract

Modeling of soil nitric oxide (NO) emissions is highly uncertain and may misrepresent its spatial and temporal distribution. This study builds upon a recently introduced parameterization to improve the timing and spatial distribution of soil NO emission estimates in the Community Multi-scale Air Quality (CMAQ) model. The parameterization considers soil parameters, meteorology, land use, and mineral nitrogen (N) availability to estimate NO emissions. We incorporate daily year-specific fertilizer data from the Environmental Policy Integrated Climate (EPIC) agricultural model to replace the annual generic data of the initial parameterization, and use a 12 km resolution soil biome map over the continental US. CMAQ modeling for July 2011 shows slight differences in model performance in simulating fine particulate matter and ozone from IMPROVE and CASTNET sites and NO_2 columns from Ozone Monitoring Instrument (OMI) satellite retrievals. We also simulate how the change in soil NO emissions scheme affects the expected O_3 response to projected emissions reductions.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

1 Introduction

Nitrogen oxides (NO_x=NO+NO_2) play a crucial role in tropospheric chemistry. Availability of NO_x influences the oxidizing capacity of the troposphere as NO_x directly reacts with hydroxyl radicals (OH) and catalyzes tropospheric ozone (O_3) production and destruction (Seinfeld and Pandis, 2012). NO_x also affects the lifetime of reactive greenhouse gases like CH_4 by influencing its dominant oxidant OH (Steinkamp and Lawrence, 2011), thus affecting the Earth's radiative balance (IPCC, 2007). NO_x also influences rates of formation of inorganic particulate matter (PM) (Wang et al., 2013) and organic PM (Seinfeld and Pandis, 2012).

Soil NO_x emissions accounts for ~15-40 % of the tropospheric NO_2 column over the continental United States (CONUS), and up to 80% in highly N fertilized rural areas like the Sahel of Africa (Hudman et al., 2012). The estimated amount of nitric oxide (NO) emitted from soils is highly uncertain, ranging from 4-15 Tg-N yr^{-1}, with different estimates of total global NO_x budget also showing a mean difference of 60-70% (Potter et al., 1996; Davidson and Kingerlee, 1997; Yienger and Levy, 1995; Jaeglé et al., 2005; Stavrakou et al., 2008; Steinkamp and Lawrence, 2011; Miyazaki et al., 2012; Stavrakou et al., 2013; Vinken et al., 2014). Soil NO_x is mainly emitted as NO through both microbial activity (biotic/enzymatic) and chemical (abiotic/non-enzymatic) pathways, with emission rates varying as a function of meteorological conditions, physicochemical soil properties, and nitrogen (N) inputs from deposition and fertilizer or manure application (Pilegaard, 2013; Hudman et al, 2012). The fraction of soil N emitted as NO varies with meteorological and soil conditions such as temperature, soil moisture content, and pH (Ludwig et al., 2001; Parton et al., 2001; van Dijk et al., 2002; Stehfest and Bouwman, 2006).

Different biome types, comprised of vegetation and soil assemblages exhibit different NO emission factors under different soil conditions and climate zones. One of the early attempts to stratify soil NO based on different biomes by Davidson and Kingerlee (1997) involved compiling over 60 articles and 100 field estimates. They clearly identified biomes associated with low NO emissions like swamps, tundra, and temperate forests, and those with high soil NO fluxes like tropical savanna/woodland and cultivated agriculture. For instance, high soil NO fluxes were observed in croplands, savannahs or woodlands, N-rich temperate forests and even boreal/tropical forests with low NO_2^- availability in warm conditions and acidic soil (Kesik et al., 2006; Cheng et al., 2007; Su et al., 2011). This approach, however, fails to capture within-

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

biome variation in NO emissions (Miyazaki et al., 2012; Vinken et al., 2014). Steinkamp and Lawrence (2011) more recently compiled worldwide emission factors from a dataset consisting of 112 articles with 583 field measurements of soil NO_x covering the period from 1976 to 2010, and regrouped them into 24 soil biome type based on MODIS land cover category as well as Köppen climate zone classifications (Kottek et al., 2006).

N deposition can be a significant driver of soil NO emissions in N-limited settings or near strong N emissions sources, where both wet and dry deposition of N species act like an additional fertilizer source (Yienger and Levy, 1995; Hudman et al., 2012). The response of soil NO_x emission to N deposition varies as a function of soil N status and land-use history of the land use/biome type. Mature forests for instance with already high initial soil N due to higher mineralization rates give higher soil NO flux than rehabilitated and disturbed ones (Zhang et al., 2008). In agricultural soils, N deposition is a leading contributor to the inorganic N pool that eventually contributes to soil NO emissions (Liu et al., 2006; Pilegaard, 2013).

Fertilizer (organic and inorganic) application represent controllable influences on soil N emissions (Pilegaard, 2013) and are leading sources of reactive nitrogen (N) worldwide (Galloway and Cowling, 2002). U.S. fertilizer use increased by nearly a factor of 4 from 1961 to 1999 (IFIA, 2001). Soil NO emissions increase with rising fertilizer application, with conversion rate of applied fertilizer N to NO_x being up to ~ 11% (Williams et al., 1988; Shepherd et al., 1991). Open and closed chamber studies have shown increasing fertilizer application to increase both NO and N_2O fluxes simultaneously, but with variability in NO/N_2O emission ratio (Harrison et al., 1995; Conrad, 1996; Veldkamp and Keller, 1997).

Meteorological conditions influence soil NO emission rates. Large pulses of biogenic NO emissions often follow the onset of rain after a dry period (Davidson, 1992; Scholes et al., 1997; Jaeglé et al., 2004; Hudman et al., 2010). Soil NO pulsing events occur when water stressed nitrifying bacteria, which remain dormant during dry periods, are activated by the first rains and start metabolizing accumulated N in the soil. NO pulses of up to 10–100 times background levels typically last for about 1–2 days (Yienger and Levy, 1995; Hudman et al., 2012).

Adsorption onto plant canopy surfaces can reduce the amount of soil NO emissions entering the broader atmosphere. Yienger and Levy (1995) (YL) soil NO scheme followed a Canopy Reduction Factor (CRF) approach (Wang et al., 1998) to account for the reduction of soil NO

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions Open Access EGU

emission flux *via* stomatal or cuticle exchange as a function of dry deposition within the canopy on a global scale.

Contemporary air quality models such as the Community Multi-scale Air Quality (CMAQ) model most often use an adaptation of the YL scheme to quantify soil NO emissions as a function of fertilizer application, soil moisture, precipitation and CRF (Byun and Schere, 2006). However, YL has been found to underestimate emissions rates inferred from satellite and ground measurements by a factor ranging from 1.5 to 4.5, and to misrepresent some key spatial and temporal features of emissions (Jaeglé et al., 2005; Wang et al., 2007; Boersma et al., 2008; Zhao and Wang, 2009; Lin, 2012; Hudman et al., 2012; Vinken et al., 2014). This overall underestimation can be attributed to several uncertainties in the modeling settings, such as inaccurate emissions coefficients, poor soil moisture data, deriving soil temperatures from ground air temperatures, neglecting nitrogen deposition and outdated fertilizer application rates (Yienger and Levy, 1995; Jaeglé et al., 2005; Delon et al., 2007; Wang et al., 2007; Boersma et al., 2008; Delon et al., 2008; Hudman et al., 2010; Steinkamp and Lawrence, 2011; Hudman et al., 2012).

The Berkley Dalhousie Soil NO Parameterization (BDSNP) scheme, originally implemented by Hudman et al. (2012) in the GEOS-Chem global chemical transport model, outperforms YL by better representing biome type, the timing of emissions, and actual soil temperature and moisture (Hudman et al., 2010).

Our approach builds upon BDSNP by using the Environmental Policy Integrated Climate (EPIC) biogeochemical model for dynamic representation of the soil N pool on a day-to-day basis. EPIC is a field scale biogeochemical process model developed by the United States Department of Agriculture (USDA) to represent plant growth, soil hydrology, and soil heat budgets for multiple soil layers of variable thickness, multiple vegetative systems and crop management practices (Cooter et al., 2012). EPIC can model up to 1 sq. km (100 ha) spatially and on a daily time scale (CMAS, 2015). EPIC simulations are compatible with spatial and temporal scale of CMAQ as well (Bash et al., 2013). EPIC accounts for different agricultural management scenarios, accurate simulation of soil conditions and plant growth to produce plan demand-driven fertilizer estimates for BDSNP (Cooter et al., 2012; Bash et al., 2013).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Baseline soil NO emission rate for each location (Hudman et al., 2012; Vinken et al., 2014), use a new soil biome map with finer-scale representation of land cover systems consistent with typical resolution of a regional model. We also built an offline version of BDSNP (stand-alone BDSNP), which can use benchmarked inputs from the CMAQ and allows quick diagnostic based on soil NO estimates for sensitivity analysis (Supplementary material Section S.2).

2 Methodology

2.1 Implementation of advanced soil NO parameterization in CMAQ

2.1.1 Land surface model (LSM)

Our implementation of the BDSNP soil NO parameterization in CMAQ uses Pleim-Xiu Land Surface Model (Pleim and Xiu, 2003). Compared to the coarser LSM in GEOS-Chem (Bey et al., 2001), Pleim-Xiu provides finer-scale estimates of soil moisture and soil temperature based on solar radiation, temperature, Leaf Area Index (LAI), vegetation coverage, and aerodynamic resistance. The rich amount of information available from the Pleim-Xiu LSM enables refined representation of soil moisture and soil temperature for implementation in soil NO parameterization.

2.1.2 Canopy reduction factor

The original implementation of BDSNP in GEOS-Chem did not provide specific spatial-temporal variation of CRF in each modeling grid, but used a monthly average CRF from Wang et al. (1998). Wang et al. (1998) included an updated CRF as part of their implementation of YL into GEOS-Chem. This CRF is based on wind speed, turbulence, canopy structure, deposition constants, and other physical variables. In the GEOS-Chem implementation of BDSNP, this CRF reduced the flux by ~ 16%, from 10.7 Tg-N yr^{-1} above soil to 9 Tg-N yr^{-1} above canopy (Hudman et al., 2012).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Our BDSNP implementation for CMAQ uses the same approach of integrating CRF as used in Wang et al. (1998) with the biome categorization based on Steinkamp and Lawrence (2011) and Köppen climate classes (Kottek et al. 2006) in the soil NO_x parametrization itself.

2.1.3 Fertilizer

YL in CMAQ assumed a linear correlation between fertilizer application and its induced emissions over general growing season, May-August in the Northern Hemisphere and November-February in the Southern Hemisphere (Yienger and Levy, 1995) rather than peaking near the time of fertilization at the beginning of the local growing season. This likely caused inaccurate temporal representation of fertilizer driven emissions in certain regions (Hudman et al., 2012). The GEOS-Chem implementation of BDSNP applied a long-term average fertilizer application with a decay term after fertilizer is applied. Constant fertilizer emissions neglect an important phenomenon: applying fertilizer during a dry period when neither plants nor bacteria may have the water available to use it may result in a large pulse when the soil is eventually re-wetted (Pilegaard, 2013). Such dry spring N fertilizer application can be quite significant, especially in the mid-west and southern plains in the US (Cooter et al., 2012). The current fertilizer data used for the BDSNP is scaled to global 2006 emissions by Hudman et al. (2012) using a spatial distribution for year 2000 from Potter et al. (2010). This global database reported by Potter et al. (2010) is already 8 years out of date in magnitude and 14 years out of date for relative distribution, and has relatively coarse resolution based on out-of-date long term average (national-level fertilizer data from 1994 to 2001). Using recent fertilizer application information is essential to soil NO estimates given the fact that N fertilizer is the major contributor to plant nutrient use in US, and its share has been increasing from 11,535 thousand short tons in 2001 to 12,840,000 short tons in 2013 (USDA ERS, 2013). Our implementation of BDSNP into CMAQ is designed to enable updates by subsequent developers to use new year- and location- specific fertilizer data. We use the Fertilizer Emission Scenario Tool for CMAQ (FEST-C v1.1, http://www.cmascenter.org) to incorporate EPIC fertilizer application data into our CMAQ runs.

2.1.4 N Deposition

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

YL in CMAQ neglects nitrogen deposition, which can result in an 0.5 Tg/yr underestimation in soil NO_x globally (~5%) (Hudman et al., 2012). The implementation of the EPIC model in FEST-C inputs oxidized and reduced form of N deposition directly into soil ammonia and nitrate pools each day. In Our implementation of BDSNP, these daily time series derive from previous CMAQ simulation. Inclusion of this deposition N source acts to reduce the simulated plant-based demand for additional N applications.

2.1.5 Formulation of soil NO scheme

Figure 1 provides the flow chart of the BDSNP scheme implementation, which has the option to run in-line with CMAQ, or offline as a stand-alone emissions parameterization. Static input files in Hudman et al. 2012 BDSNP implementation (labelled as 'old' in Fig. 1) such as those giving soil biome type with climate zone and global fertilizer pool are needed to determine the soil base emission value at each modeling grid. The Meteorology-Chemistry Interface Processor (MCIP) (Otte and Pleim, 2010) takes outputs from a meteorological model such as Weather Research and Forecasting (WRF) model (Skamarock et al., 2008) to provide a complete set of meteorological data needed for emissions and air quality simulations.

There are seven key input environment variables and two key output environment variables in our implementation of BDSNP. Table S1 lists their names and corresponding functionalities.

Our implementation of the BDSNP soil NOx emission, S_{NO_x} in CMAQ multiplies a base emission factor (A) by scaling factors dependent on soil temperature (T) and soil moisture (θ), i.e., $f(T)$, $g(\theta)$ and a pulsing term (P) (equation 1). The base emission factor depends on biome type under wet or dry soil conditions. The pulsing term depends on the length of the dry period, rather than the accumulated rainfall amount considered by YL. The CRF term estimate the fractional reduction in soil NO_x flux due to canopy resistance.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

$$S_{NO_x}\, Flux(\frac{ng\,N}{m^2 s}) =$$

$$A'_{biome}(N_{avail}) \times f(T) \times g(\theta) \times P(l_{dry}) \times CRF(LAI, Meterology, Biome) \quad (1)$$

$$A'_{biome} = A_{biome} + N_{avail} \times \bar{E} \quad (2)$$

$$N_{avail}(t) = N_{avail\,Fert}(0) \times e^{-\frac{t}{\tau_1}} + F \times \tau_1 \times \left(1 - e^{-\frac{t}{\tau_1}}\right) + N_{avail\,Dep}(0) \times e^{-\frac{t}{\tau_2}} + D \times \tau_2 \times (1 - e^{-\frac{t}{\tau_2}})$$

(3)

Fertilizer and deposition both contribute to modifying the A'_{biome} emissions coefficients for each biome. Available nitrogen (N_{avail}) at time t from fertilizer and deposition is multiplied by emission rate, $\bar{E}$, based on the observed global estimates of fertilizer emissions (~ 1.8 Tg-N yr^{-1}) by Stehfest and Bouwman (2006) and added to biome specific soil NO emission factors (A_{biome}) from Steinkamp and Lawrence (2011) to give the net base emission factor (A'_{biome}) (Eq. (2) and Eq. (3)). The resulting A' is multiplied by the meteorological scaling or response factors: $f(T)$, $g(\theta)$, and $P(l_{dry})$ as in Eq. (1). The soil temperature response or scaling factor $f(T)$ is simplified to be exponential everywhere. NO flux now depends on soil moisture (θ) instead of rainfall, and it increases smoothly to a maximum value before decreasing as the ground becomes water saturated. In Eq. (3), F is fertilization rate (kg ha^{-1}), D is the wet and dry deposition rate (kg ha^{-1}) considered as an additional fertilization rate, and τ is decay time, which is 4 months for fertilizer (τ_1) and 6 months for deposition (τ_2) (Hudman et al. 2012).

BDSNP uses a Poisson function to represent the dependence of emission rates on soil moisture (θ), where the parameters 'a' and 'b' vary for different climates such that the maximum of the function occurs at $\theta = 0.2$ for arid soils and $\theta = 0.3$ otherwise (Hudman et al. 2012). We adopt the same approach in CMAQ, as follows:

$$f(T) * g(\theta) = e^{0.103*T} * a * \theta * e^{-b*\theta^2} \quad (4)$$

The pulsing term depends on the length of the dry period (l_{dry}) and a change in soil moisture instead of on the amount of precipitation (Hudman et al., 2012).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

The pulsing term for emissions when rain follows a dry period is

$$P(l_{dry}, t) = [13.01 * \ln(l_{dry}) - 53.6] * e^{-c*t} \quad (5)$$

In this equation, l_{dry} is the length of the dry period that preceded the rain and c = 0.068 hour^{-1} defines the exponential decay of the pulse.

Beyond this basic implementation of the above stated BDSNP framework into CMAQ, there were major modifications (highlighted as 'new' in Fig. 1) in the form of: a) updating biome map consistent with CMAQ, b) incorporating year- and location- specific fertilizer data using EPIC outputs and c) development of a standalone BDSNP module. Our work focuses on those developments discussed in detail in the sections to follow.

2.2 Soil biome map over CONUS

The original implementation of BDSNP used the global soil biome data from the GEOS-Chem, with emission factors for each biome under dry/wet conditions taken from Steinkamp and Lawrence (2011) (Appendix Table A1). Our implementation in CMAQ uses a finer resolution (12 km) soil biome map over CONUS. The map is generated from the 30-arc-second (approximately 1 kilometer) NLCD40 (National Land Cover Dataset) for 2006, with 40 land cover/land use classifications. A mapping algorithm table (see Appendix Table A2) was created to connect the land use category to soil biome type (Table A1) based on best available knowledge. For the categories with identical names, such as 'evergreen needleleaf forest', 'deciduous needleleaf forest', 'mixed forest', 'savannas' and 'grassland', the mapping is direct. Categories in NLCD40, which are subsets of the corresponding biome category, are consolidated into one category by addition. For example, 'permanent snow and ice' and 'perennial ice-snow' in NLCD40 are combined to form 'snow and ice'; 'developed open space', 'developed low intensity', 'developed medium intensity', and 'developed high intensity' are added to form 'urban and built-up lands'. For the categories appearing only in NLCD40, the mapping algorithm is determined by referring to the CMAQ mapping scheme, available in Cross-Section and Quantum Yield (CSQY) data files in the CMAQ coding. One such case is to map 'lichens' and

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

'moss' in NLCD40 to the category 'grassland' in soil biome. Furthermore, a model resolution compatible Köppen climate zone classification (Kottek et al., 2006) was added to allocate different emission factor for the same biome type e.g. to account for different altitudes of 'grassland' at different locations. There are five climate zone classifications, namely A: equatorial, B: arid, C: warm temperature, D: snow, E: polar. A 12 km CONUS model resolution climate zone classification map (see Figure 2) was created using the Spatial Allocator based on the county level climate zone definition as the surrogate based on a dominant land use, (http://koeppen-geiger.vu-wien.ac.at/data/KoeppenGeiger.UScounty.txt).

Figure 2 compares the 24 soil biome map with 0.25 degree resolution from the GEOS-Chem settings to the new 12 km resolution soil biome map we created here for CMAQ. Table A2 gives the biome type names with corresponding climate zones.

The classification of simulation domain into arid and non-arid region with consistent resolution is also included in our implementation. Figure B1 shows the distribution of arid (red) and non-arid (blue) regions. For the modeling grid classified as 'arid' region, the maximum moisture scaling factor corresponds to the water-filled pore space (θ) value equal to 0.2; while for the 'non-arid' modeling grid, the maximum moisture scaling factor corresponds with θ=0.3 (Hudman et al., 2012).

2.3 Representation of fertilizer N

We implemented two approaches for representing fertilizer N. The first approach regrids fertilizer data from the global GEOS-Chem BDSNP implementation (Hudman et al. 2012) to our 12 km resolution CONUS domain. That scheme uses the global fertilizer database from Potter et al. (2010) and assumed 37% of fertilizer and manure N is available (1.8 Tg-N yr^{-1}) for potential emission. Figure B2 provides the day-by-day variation of total N remaining due to fertilizer application over CONUS during a year, and shows the typical cycle between growing season and non-growing season. The Potter data, however, are a decade old and at coarse resolution for county-level in US.

Our second approach (Figure 3) uses the EPIC model as implemented in the FEST-C tool (Cooter et al. 2012) to provide a dynamic representation of fertilizer applications for a specific growing season. FEST-C (v1.1) generates model-ready fertilizer input files for CMAQ. . Use of

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

FEST-C/EPIC instead of soil emissions from YL scheme has been shown to improve CMAQ performance for nitrate and ammonia in CONUS (Bash et al., 2013). The BELD4 tool in FEST-C system was used to provide the crop usage fraction over our domain. We summed FEST-C data for ammonia, nitrate and organic, T1_ANH3, T1_ANO3 and T1_AON respectively in kg-N/ha, to give a total soil N pool for each of 42 simulated crops (CMAS, 2015). This daily crop-wise total soil N pool was then weighted by the fraction of each crop type at each modeling grid to get a final weighted sum total soil N pool usable in BDSNP. CMAQ v.5.0.2 can be run with in-line biogenic emissions, calculated in tandem with the rest of the model. Since the EPIC N pools already include N deposition, we designed our soil NO emissions module to be flexible in recognizing whether it is using fertilizer data such as Potter et al. (2010) that does not include deposition or EPIC that does.

Figure 4 compares the FEST-C derived N fertilizer map and the default coarser resolution long-term average fertilizer map from Potter. While the spatial patterns are similar, EPIC provides finer resolution and more up-to-date information.

2.4 Model configurations and data use for model evaluations

The CMAQ domain settings for CONUS as provided by the EPA were used to simulate the whole month of July in 2011. July corresponds to the month of peak flux for soil nitrogen emissions in the United States (Williams et al., 1992; Cooter et al., 2012; Bash et al., 2013) and is an active period for ozone photochemistry (Cooper et al., 2014; Strode et al., 2015).

A ten day (21 June-30 June, 2011) spin-up time was used to minimize the influence from initial conditions. The domain consisted of 396 columns, 246 rows, 26 vertical layers, and 12 km rectangular cells using a Lambert Conformal Projection over North America. This configuration was consistent throughout the WRF-BDSNP-CMAQ modeling framework (see Figure 1). Meteorology data were produced through the WRF Model nudged to National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research Reanalysis (NARR) data, which is comprised of historical observations and processed to control quality and consistency across years by National Oceanic and Atmospheric Administration (NOAA).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Emissions were generated using the Sparse Matrix Operator Kernel Emissions (SMOKE) model (CMAS, 2014) and 2011NEIv1.

We applied CMAQ with three sets of soil NO emissions: a) Standard YL soil NO scheme, b) BDSNP scheme with Potter et al. (2010) fertilizer data set and biome mappings from GEOS-Chem, and c) BDSNP scheme with EPIC 2011 data and new biome mappings. Within these three cases, we simulated the impact of anthropogenic NO_x reductions applied to all contributing source sectors listed in the 2011 National Emission Inventory (NEI). For this purpose, we considered the baseline NO_x reduction scenario from 2011 to 2025 that EPA's Regulatory Impact Analysis (RIA) determined for Business as Usual (BAU) in the CONUS domain (Figure 2A-1, Table 2A-1 in https://www3.epa.gov/ttn/ecas/docs/20151001ria.pdf). Table 1 gives a full list of modeling configurations settings used for achieving the above-mentioned simulations.
Model simulations were evaluated against the following in situ and satellite-based data: 16 USEPA Clean Air Status and Trends Network (CASTNET) sites for MDA8 O_3 (www.epa.gov/castnet), 9 Interagency Monitoring of Protected Visual Environments (IMPROVE) sites for daily average $PM_{2.5}$ (Malm et al., 1994), and NASA's OMI retrieval product for tropospheric NO_2 column (Bucsela et al., 2013; Lamsal et al., 2014). Fig. 5 shows the spatial distribution of the ground sites used for validation of modeled estimates. The selected ground sites for model validation are mostly based in agricultural regions with intense fertilizer application rate and high NO fluxes, specifically the Midwest, southern plains, and San Joaquin Valley.

We also simulated three sensitivity cases for the same time period and domain with the offline soil NO module: a) NLCD40 based (new) biome vs GEOS-Chem based (old) biome (using EF1 in Table A1), b) EPIC 2011 vs Potter data and, c) Global mean biome emission factor (EF1 in Table A1) vs North American mean emission factor (EF3 in Table A1) (Supplementary material Section S.3).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

3 Results and Discussion

3.1 Spatial distribution of nitrogen fertilizer application and soil NO emissions over CONUS

We demarcated the CONUS domain into six sub-domains (Figure 6) to analyze model outputs. The updated BDSNP model and EPIC fertilizer result in higher soil NO emission rates than YL and Potter. Emissions increase by a factor ranging from 1.8 to 2.8 in shifting from YL to BDSNP, even while retaining the Potter fertilizer data and original biome map, indicating that the shift from YL to BDSNP scheme is the largest driver of the increase in emissions estimates. EPIC and the new biome dataset further increase emissions over most of CONUS, except for the southwest region. In Midwest and Western US, the new biome map identified more cropland and shifted some grasslands to other land cover types such as forests, savannah and croplands, which exhibit higher soil NO emissions (Figure 2; Table A1). The Midwest region is characterized with the highest emission rate due to its abundant agricultural lands with high fertilizer application rates (Figure 4).

3.2 Evaluation of CMAQ NO_2 with satellite OMI NO_2 observations

The standard (version 2.1) OMI tropospheric NO_2 column observations from NASA's Aura satellite as discussed in Bucsela et al. (2013) and Lamsal et al. (2014) were used for comparison with our modelled NO_2 vertical columns. To enable comparison, the quality-assured, clear-sky (cloud radiance fraction < 0.5) OMI NO_2 data were gridded and projected to our domain by using ArcGIS 10.3. CMAQ modelled NO_2 column densities in molecules per cm^2 were derived using vertical integration and extracted for 13:00-14:00 local time, corresponding to the time of OMI measurements.

We compared CMAQ simulated tropospheric NO_2 columns with OMI product for regions showing highest sensitivity in soil NO switching from YL to BDSNP: Midwest, San Joaquin Valley in California and central Texas (see Appendix Figure B3). Switching from YL to our updated BDSNP ('new') module improved agreement with OMI NO_2 columns in central Texas

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions Open Access EGU

but over-predicts column NO_2 in the San Joaquin Valley and Midwest (Figure 7). Even the YL estimate was higher than OMI by a factor of two in the Midwest (Figure 7).

3.3 Evaluation with $PM_{2.5}$ and ozone observations

Model results are compared with observational data from IMPROVE monitors for $PM_{2.5}$ and CASTNET monitors for ozone. We first compute differences between ozone and $PM_{2.5}$ estimates from the three simulation cases to identify sites influenced by the choice of soil NO scheme during our July 2011 episode (Figures 8 and 9). These highlights nine IMPROVE sites for $PM_{2.5}$ and 16 CASTNET sites for ozone (Figures 5, 8 and 9) where CMAQ results are sensitive to soil NO changes (Figure 6).

Statistical comparisons of modeled and observed daily average $PM_{2.5}$ at the nine IMPROVE sites are provided in Table 2. Mean Absolute Gross Error (MAGE) and Root Mean Square Error (RMSE) improved from 2.8 to 2.7 ug/m^3 and 3.4 to 3.3 ug/m^3 respectively when moving from YL to BDSNP with the new inputs. Both Pearson's and Spearman's ranked correlation coefficient (R) shows no significant change when soil NO module in CMAQ is switched from YL to BDSNP (Potter with old biome) and BDSNP (EPIC with new biome) (Tables 2). Use of the ranked correlation coefficient minimizes the impact of spurious correlations due to outliers but does not affect the analysis. Switching from YL to our updated BDSNP ('new') module shows that the predicted versus observed fit becomes slightly closer to 1:1 (Figure 10). Numerical Mean Bias (NMB) and Numerical Mean Error (NME) improve from -28.5% to -26.4% and 34.6% to 33.6%, respectively.

In contrast to the $PM_{2.5}$ results, the updated soil NO scheme yields mixed impacts on model performance for maximum daily average 8-hour (MDA8) ozone at the targeted 16 CASTNET sites (Table 3 and Figure 11). For the 11 agricultural/prairie sites, replacement of YL with BDSNP with new inputs increases NMB from 7.6% to 14.1% and NME from 15.7 to 19.3% (Table 3). The excess ozone may occur because FEST-C does not account for the loss of fertilizer N to the water stream ("tile drainage") in wet conditions (Dinnes et al., 2002). Hudman et al. (2012) suggested $\theta = 0.175$ (m^3/m^3) as threshold below which dry condition occur. During July 2011, in Midwest monthly mean soil moisture (θ_{mean}, m^3/m^3) is mostly > 0.175, indicating possibility of wet conditions (Fig. S5). This can also be due to known wet bias in WRF simulated meteorology i.e. more perceived precipitation than observed (Zhang et al., 2009) which may result in high NO emissions in moist soils. Overestimation of O_3 is due to higher NO emissions, as these regions comprise of mostly NO_x limited rural locations.

At the California CASTNET sites, BDSNP enhances model performance in simulating observed MDA8 ozone (Table 3). This can be seen in the NMB, NME, MAGE, and RMSE comparisons between YL and BDSNP, though updating BDSNP to the newer inputs does not enhance performance (Table 3).

3.4 Impact of soil NO scheme on ozone sensitivity to anthropogenic NO_x perturbations

We analyzed how the choice of soil NO parameterization affects the responsiveness of ozone to reductions in anthropogenic NO_x emissions. We applied emission perturbation factors based on the 5.7 million ton reduction in baseline anthropogenic NO_x emissions from 2011 to 2025 that US EPA simulated in its latest RIA (U.S. EPA, 2015). Table 4 gives the perturbation factors we used to obtain baseline anthropogenic NO_x emissions for 2025 over all contributing sectors as listed from NEI 2011. Since our simulation is for July 2011 over CONUS, we used these perturbation factors rather than the net reductions in RIA to scale emissions in a similar pattern as given in RIA for annual baseline perturbations from 2011 to 2025 with BAU.

Shifting from YL to the BDSNP soil NO scheme reduces the sensitivity of MDA8 O_3 to anthropogenic NO_x perturbations. The impacts are greatest in California and the Midwest, where shifting to BDSNP can reduce the expected impact of the anthropogenic NO_x reductions by ~ 1 to 1.5 ppbV. Changing the inputs within the BDSNP scheme has a smaller impact (Figure 12). Our results imply that the higher soil NO emissions from our updated BDSNP module shifts the ozone photochemistry to a less strongly NO_x-limited regime.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

4 Conclusions

Our BDSNP implementation represents a substantial update from the YL scheme for estimating soil NO in CMAQ. Compared to the previous implementation of BDSNP in global GEOS-Chem model, our implementation in CMAQ incorporated finer-scale representation of its dependence on land use, soil conditions, and N availability. This finer resolution and updated biome and fertilizer data set resulted in higher sensitivity of soil NO to biome emission factors. Our updated BDSNP scheme (EPIC and new biome) predicts slightly higher soil NO than the inputs used in GEOS-Chem, primarily due to the use of 2011 daily EPIC/FEST-C fertilizer data and fine resolution NLCD40 biomes (Figure 6).

Sensitivities to different input datasets were examined using our standalone BDSNP module to reduce computational cost. Switching from GEOS-Chem biome to new NLCD40 biome drops soil NO in the northwest and southwest portions of our domain due to the finer resolution biome map exhibiting lower emission factors in those regions. Replacing fertilizer data from Potter et al. (2010) with an EPIC 2011 dataset increased soil NO mostly in the Midwest (Supplementary material Figure S4).

We compared tropospheric NO_2 column densities output from our CMAQ runs with the three inline soil NO schemes to OMI observations as spatial average over regions sensitive to switch from YL to our updated BDSNP scheme. Temporal average of OMI and CMAQ simulated NO_2 column densities was done over the OMI overpass time (13:00-14:00 local time) for July 2011 monthly mean. Figure 7 summarizes tropospheric NO_2 column density comparisons between model and OMI satellite observation for aforementioned sensitive regions. Central Texas showed improvement with switch from YL to our BDSNP ('new') scheme. For July 2011, central Texas and San Joaquin Valley exhibit relatively dry soil conditions, whereas the Midwest was mostly wet (Supplementary material Figure S5). Even with similar conditions as central Texas, San Joaquin region shows overall degradation. Overestimation of simulated NO_2 columns up to twice of OMI over Midwestern US and San Joaquin valley for summer episodes has been exhibited earlier as well (Lamsal et al., 2014). Several factors, such as spatial inhomogeneity within OMI pixels and possible errors arising from the stratosphere-troposphere separation scheme and air mass factor calculations, can be attributed to this overestimation. Retrieval difficulties in complex terrain may explain the discrepancies in NO_2 column over San Joaquin Valley even though it shows slight improvement with updates within BDSNP ('old' to 'new') and has similar dry conditions as central Texas.

We examined the performance of CMAQ under each of the soil NO parameterizations. Regions where soil NO parameterizations most impacted MDA8 ozone and $PM_{2.5}$ were examined for model performance in simulating CASTNET MDA8 O_3 and IMPROVE $PM_{2.5}$ observations.

For $PM_{2.5}$, our updated BDSNP module ('new') showed the best performance (Table 2). Evaluations against MDA8 O_3 observations found contrasting behavior for two different sets of CASTNET sites. The 11 mostly agricultural and prairie sites extending across the Midwest and southern US showed consistent overestimation as we moved from YL to BDNSP with new inputs, with bias jumping from ~ 7% to 14% and error from 15% to 19% (Table 3). However, the 5 forest/national park sites most of which lie near the San Joaquin Valley by contrast showed an overall improvement in bias from ~ 13% to 10% and in error from ~ 17 % to 15% (Table 3).

Over-predictions of soil NO emissions especially in wet conditions may result from EPIC not properly accounting for on-farm nitrogen management practices like tile drainage. Crops such as alfalfa, hay, grass, and rice experience soil N loss due to tile drainage in wet soils (Gast et al., 1978; Randall et al., 1997). Recent updates to FEST-C (v. 1.2) include tile drainage for some crops but not hay, rice, grass and alfalfa (CMAS, 2015). Tile drainage results in loss of fertilizer N to water run-off from wet or moist soils.

We analyzed how the soil NO schemes affect the sensitivity of MDA8 ozone to anthropogenic NO_x reductions by considering the 5.7 million tons/year reduction from 2011 levels that U.S. EPA expects for United States by 2025 with BAU scenario. These reductions were applied on basis of perturbation factors of relevant sectors keeping biogenic emissions unchanged for July 2011, based on EPA's annual baseline estimates between 2011 and 2025 (Table 4). These anthropogenic NO_x reductions yield less reduction in MDA8 O_3 under the BDNSP soil NO scheme than YL, with 1-2 ppbv differences over parts of California and the Midwest (Figure 12). The shift occurs because our updated BDSNP schemes have higher soil NO in these regions, pushing them toward less strongly NO_x-limited regimes.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

This work represents crucial advancement toward enhanced representation of soil NO in a regional model. Although possible wet biases and using dominant land cover rather than fractional in soil biome classification, may have over-predicted NO in agricultural regions in present study. The EPIC simulation used here lacks complete representation of farming management practices like tile, which can reduced soil moisture and soil NO fluxes. Inclusion of biogeochemistry influencing different reactive N species encompassing the entire N cycling could enable more mechanistic representation of emissions. For future work, there is a need for more accurate representation of actual farming practices and internalizing updated soil reactive N bio-geochemical schemes. More field observations are needed as well in order to increase the sample size for evaluation of modeled estimates soil emissions of reactive N species beyond NO.

Code availability

The modified and new scripts used for implementation of BDSNP in CMAQ Version 5.0.2 are in the supplementary material. Also provided as supplement is the user manual giving details on implementing BDSNP module in-line with CMAQ, as used in this work. Source codes for CMAQ version 5.0.2 and FEST-C version 1.1 are both open-source, available with applicable free registration at http://www.cmascenter.org. Advanced Research WRF model (ARW) version 3.6.1 used in this study is also available as a free open-source resource at http://www2.mmm.ucar.edu/wrf/users/download/get_source.html.

Acknowledgements

This work was supported by NASA's Air Quality Applied Sciences Team through a tiger team project grant for DYNAMO: DYnamic Inputs of Natural Conditions for Air Quality Models. Although this work was reviewed by EPA and approved for publication, it may not necessarily reflect official Agency policy.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

References

Bash, J., Cooter, E., Dennis, R., Walker, J., and Pleim, J.: Evaluation of a regional air-quality model with bidirectional NH 3 exchange coupled to an agroecosystem model, Biogeosciences, 10, 1635-1645, 2013.

Bey, I., Jacob, D. J., Yantosca, R. M., Logan, J. A., Field, B., Fiore, A. M., Li, Q., Liu, H., Mickley, L. J., and Schultz, M.: Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation, J. Geophys. Res., 106, 23,073-23,096, 2001.

Boersma, K., Jacob, D. J., Bucsela, E., Perring, A., Dirksen, R., Yantosca, R., Park, R., Wenig, M., Bertram, T., and Cohen, R.: Validation of OMI tropospheric NO 2 observations during INTEX-B and application to constrain NO_x emissions over the eastern United States and Mexico, Atmospheric Environment, 42, 4480-4497, 2008.

Bucsela, E. J., Krotkov, N. A., Celarier, E. A., Lamsal, L. N., Swartz, W. H., Bhartia, P. K., Boersma, K. F., Veefkind, J. P., Gleason, J. F., and Pickering, K. E.: A new stratospheric and tropospheric NO2 retrieval algorithm for nadir-viewing satellite instruments: applications to OMI, Atmos. Meas. Tech., 6, 2607-2626, doi:10.5194/amt-6-2607-2013, 2013.

Byun, D. W. and Schere, K. L.: Review of the governing equations, computational algorithms, and other components of the models- 3 Community Multiscale Air Quality (CMAQ) modeling system, Appl. Mech. Rev., 59, 51–77, 2006.

Conrad R. Soil microorganisms as controllers of atmospheric trace gases (H_2, CO, CH_4, OCS, N_2O, and NO). *Microbiological Reviews*. 60(4):609-640; 1996.

Cooper, O.R., Parrish, D.D., Ziemke, J., Balashov, N.V., Cupeiro, M., Galbally, I.E., Gilge, S., Horowitz, L., Jensen, N.R., Lamarque, J.F. and Naik, V.: Global distribution and trends of tropospheric ozone: An observation-based review. Elementa: Science of the Anthropocene, 2(1), p.000029, 2014.

Cheng, J.-l., Zhou, S., and Zhu, Y.-w.: Assessment and mapping of environmental quality in agricultural soils of Zhejiang Province, China, Journal of Environmental Sciences, 19, 50-54, 2007.

CMAS, Sparse Matrix Operators Kernel Emissions model (SMOKE) version 3.6, University of North Carolina at Chapel Hill Institute for the Environment, Center for Environmental Modeling for Policy

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

Development (CEMPD), Community Modeling and Analysis System Center (CMAS), Chapel Hill, NC (http://www.smoke-model.org), 2014.

CMAS 2015: User's Guide for the Fertilizer Emission Scenario Tool for CMAQ (FEST-C) Version 1.2, Institute of Environment, The University of North Carolina at Chapel Hill, Chapel Hill, NC, available at: https://www.cmascenter.org/fest-c/documentation/1.2/FESTC1_2_userManual.pdf, last accessed: 30 September, 2015

Cooter, E. J., Bash, J.O., Benson, V., and Ran, L.: Linking agricultural crop management and air quality models for regional to national-scale nitrogen assessments. *Biogeosciences*, 9, no. 10: 4023-4035, 2012.

Davidson, E.: Pulses of nitric oxide and nitrous oxide flux following wetting of dry soil: an assessment of probable sources and importance relative to annual fluxes, Ecol. Bull., 42, 149–155, 1992.

Davidson, E. and Kingerlee, W.: A global inventory of nitric oxide emissions from soils, Nutr. Cycl. Agroecosys., 48, 37–50, doi:10.1023/A:1009738715891, 1997.

Delon, C., Serça, D., Boissard, C., Dupont, R., Dutot, A., Laville, P., De Rosnay, P., and Delmas, R.: Soil NO emissions modelling using artificial neural network, Tellus B, 59, 502-513, 2007.

Delon, C., Reeves, C., Stewart, D., Serça, D., Dupont, R., Mari, C., Chaboureau, J.-P., and Tulet, P.: Biogenic nitrogen oxide emissions from soils–impact on NO x and ozone over West Africa during AMMA (African Monsoon Multidisciplinary Experiment): modelling study, Atmospheric Chemistry and Physics, 8, 2351-2363, 2008.

Dinnes, D. L., Karlen, D. L., Jaynes, D. B., Kaspar, T. C., Hatfield, J. L., Colvin, T. S., and Cambardella, C. A.: Nitrogen management strategies to reduce nitrate leaching in tile-drained Midwestern soils, Agronomy journal, 94, 153-171, 2002.

Galloway, J. N., and Cowling, E. B.: Reactive nitrogen and the world: 200 years of change, AMBIO: A Journal of the Human Environment, 31, 64-71, 2002.

Gast, R., Nelson, W., and Randall, G.: Nitrate accumulation in soils and loss in tile drainage following nitrogen applications to continuous corn, Journal of environmental quality, 7, 258-261, 1978.

Harrison, R. M., Yamulki, S., Goulding, K., and Webster, C.: Effect of fertilizer application on NO and N2O fluxes from agricultural fields, Journal of Geophysical Research: Atmospheres (1984–2012), 100, 25923-25931, 1995.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Hudman, R. C., Moore, N. E., Mebust, A. K., Martin, R. V., Russell, A. R., Valin, L. C., and Cohen, R. C.: Steps towards a mechanistic model of global soil nitric oxide emissions: implementation and space based-constraints, Atmos. Chem. Phys., 12, 7779– 7795, doi:10.5194/acp-12-7779-2012, 2012. Hudman, R. C., Russell, A. R., Valin, L. C., and Cohen, R. C.: Interannual variability in soil nitric oxide emissions over the United States as viewed from space, Atmos. Chem. Phys., 10, 9943– 9952, doi:10.5194/acp-10-9943-2010, 2010.

IFIA: International Fertilizer Industry Association 2001. Nitrogen, phosphate and potash statistics.(http://www.fertilizer.org/ifa/statistics/IFADATA/dataline.asp), 2001.

IPCC: Climate Change 2007: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Parry, M. L., Canziani, O. F., Palutikof, J. P., van der Linden, P. J., and Hanson, C. E., Cambridge University Press, Cambridge, UK, 976 pp., 2007.

Jacob, D. I., and Bakwin, P. S.: Cycling of NO_x in tropical forest canopies, in Microbial Production and Consumption of Greenhouse Gases: Methane, Nitrogen Oxides and Halomethanes, edited by J. E. Rogers, and W. B. Whitman, pp. 237–253, Am. Soc. of Microbiol., Washington, D. C., 1991.

Jaeglé, L., Martin, R. V., Chance, K., Steinberger, L., Kurosu, T. P., Jacob, D. J., Modi, A. I., Yoboué, V., Sigha-Nkamdjou, L., and Galy-Lacaux, C.: Satellite mapping of rain-induced nitric oxide emissions from soils, J. Geophys. Res.-Atmos., 109, D21310, doi:10.1029/2004JD004787, 2004.

Jaeglé, L., Steinberger, L., Martin, R. V., and Chance, K.: Global partitioning of NO x sources using satellite observations: Relative roles of fossil fuel combustion, biomass burning and soil emissions, Faraday Discussions, 130, 407-423, 2005.

Kesik, M., Blagodatsky, S., Papen, H., and Butterbach-Bahl, K.: Effect of pH, temperature and substrate on N2O, NO and CO2 production by Alcaligenes faecalis p, Journal of applied microbiology, 101, 655-667, 2006.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., and Rubel, F.: World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitshrift*, 15, 259-263. DOI: 10.1127/0941-2948/2006/0130, 2006.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Lamsal, L., Krotkov, N., Celarier, E., Swartz, W., Pickering, K., Bucsela, E., Gleason, J., Martin, R., Philip, S., and Irie, H.: Evaluation of OMI operational standard NO 2 column retrievals using in situ and surface-based NO 2 observations, Atmospheric Chemistry and Physics, 14, 11587-11609, 2014.

Lin, J.-T.: Satellite constraint for emissions of nitrogen oxides from anthropogenic, lightning and soil sources over East China on a high-resolution grid, Atmospheric Chemistry and Physics, 12, 2881-2898, 2012.

Liu, X., Ju, X., Zhang, Y., He, C., Kopsch, J., and Fusuo, Z.: Nitrogen deposition in agroecosystems in the Beijing area, Agriculture, ecosystems & environment, 113, 370-377, 2006.

Ludwig, J., Meixner, F., Vogel, B., and Förstner, J.: Soil-air exchange of nitric oxide: an overview of processes, environmental factors, and modeling studies, Biogeochemistry, 52, 225–257, doi:10.1023/A:1006424330555, 2001.

Miyazaki, K., Eskes, H. J., and Sudo, K.: Global NO_x emission estimates derived from an assimilation of OMI tropospheric NO2 columns, Atmos. Chem. Phys., 12, 2263–2288, doi:10.5194/acp- 12-2263-2012, 2012.

Malm, W. C., Sisler, J. F., Huffman, D., Eldred, R. A., and Cahill, T. A.: Spatial and seasonal trends in particle concentration and optical extinction in the United States, JOURNAL OF GEOPHYSICAL RESEARCH-ALL SERIES-, 99, 1347-1347, 1994.

Otte, T. L. and Pleim, J. E.: The Meteorology-Chemistry Interface Processor (MCIP) for the CMAQ modeling system: updates through MCIPv3.4.1, Geosci. Model Dev., 3, 243-256, doi:10.5194/gmd-3-243-2010, 2010.

Parton, W. J., Holland, E. A., Del Grosso, S. J., Hartman, M. D., Martin, R. E., Mosier, A. R., Ojima, D. S., and Schimel, D. S.: Generalized model for NO_x and N_2O emissions from soils, J. Geophys. Res.-Atmos., 106, 17403–17419, doi:10.1029/2001JD900101, 2001.

Pilegaard, K.: Processes regulating nitric oxide emissions from soils, Philosophical Transactions of the Royal Society B: Biological Sciences, 368, 20130126, 2013.

Pleim, J.E. and Xiu, A.: Development of a land surface model. Part II: Data assimilation. Journal of Applied Meteorology, 42(12), pp.1811-1822, 2003.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

Potter, C., Matson, P., Vitousek, P., and Davidson, E.: Process modeling of controls on nitrogen trace gas emissions from soils worldwide, J. Geophys. Res.-Atmos., 101, 1361–1377, doi:10.1029/95JD02028, 1996.

Potter, P., Navin, R., Elena M. B., and Simon D. D.: Characterizing the spatial patterns of global fertilizer application and manure production. *Earth Interactions*, 14, no. 2: 1-22, 2010.

Randall, G., Huggins, D., Russelle, M., Fuchs, D., Nelson, W., and Anderson, J.: Nitrate losses through subsurface tile drainage in conservation reserve program, alfalfa, and row crop systems, Journal of Environmental Quality, 26, 1240-1247, 1997.

Scholes, M., Martin, R., Scholes, R., Parsons, D., and Winstead, E.: NO and N_2O emissions from savanna soils following the first simulated rains of the season, Nutr. Cycl. Agroecosys., 48, 115– 122, doi:10.1023/A:1009781420199, 1997.

Seinfeld, John H., and Spyros N. Pandis. Atmospheric chemistry and physics: from air pollution to climate change. John Wiley & Sons, 2012.

Shepherd, M., Barzetti, S., and Hastie, D.: The production of atmospheric NO x and N 2 O from a fertilized agricultural soil, Atmospheric Environment. Part A. General Topics, 25, 1961-1969, 1991.

Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X., Wang, W., and Powers, J. G.: A description of the advanced research WRF version 3, NCAR Tech. Note, NCAR/TN-475+STR, 8 pp., Natl. Cent. for Atmos. Res., Boulder, Colo., 2008 (available at: http://www.mmm.ucar.edu/wrf/users/docs/arw_v3.pdf)

Stehfest, E., & Bouwman, L.: N_2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. Nutrient Cycling in Agroecosystems, 74(3), 207-228.doi: 10.1007/s10705-006-9000-7, 2006.

Steinkamp, J., & Lawrence, M. G.: Improvement and evaluation of simulated global biogenic soil NO emissions in an AC-GCM. Atmospheric Chemistry and Physics, 11(12), 6063–6082. doi:10.5194/acp-11-6063-2011, 2011.

Stavrakou, T., Müller, J.-F., Boersma, K. F., De Smedt, I., and van der A, R. J.: Assessing the distribution and growth rates of NO_x emission sources by inverting a 10 year record of NO2 satellite columns, Geophys. Res. Lett., 35, L10801, doi:10.1029/2008GL033521, 2008.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Stavrakou, T., Müller, J.F., Boersma, K. F., van der A, R. J., Kurokawa, J., Ohara, T., and Zhang, Q.: Key chemical NO_x sink uncertainties and how they influence top-down emissions of nitrogen oxides, Atmos. Chem. Phys., 13, 9057–9082, doi:10.5194/acp-13-9057-2013, 2013.

Strode, S. A., Rodriguez, J. M., Logan, J. A., Cooper, O. R., Witte, J. C., Lamsal, L. N., Damon, M., Van Aartsen, B., Steenrod, S. D., and Strahan, S. E.: Trends and variability in surface ozone over the United States, J. Geophys. Res. Atmos., 120, 9020–9042, doi:10.1002/2014JD022784, 2015.

Su, H., Cheng, Y., Oswald, R., Behrendt, T., Trebs, I., Meixner, F. X., Andreae, M. O., Cheng, P., Zhang, Y., and Pöschl, U.: Soil nitrite as a source of atmospheric HONO and OH radicals, Science, 333, 1616-1618, 2011.

USDA ERS: USDA ERS (United States Department of Agriculture, Economic Research Service) Data sets: U.S. fertilizer use and price. Last updated July 12, 2013. http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx, 2013.

U.S. Environmental Protection Agency, Clean Air Markets Division, Clean Air Status and Trends Network (CASTNET)[Ozone 8-Hour Daily Max] available at www.epa.gov/castnet. Date accessed: [July, 2011]

U.S. EPA : U.S. Environmental Protection Agency, 2015. Regulatory Impact Analysis of the Final Revisions to the National Ambient Air Quality Standards for Ground-Level Ozone. EPA-452/R-15-007. Office of Air Quality Planning and Standards, Research Triangle Park, NC. Last updated: March, 2016. Available at: https://www3.epa.gov/ttn/ecas/docs/20151001ria.pdf .

van Dijk, S. M., A. Gut, G. A. Kirkman, B. M. Gomes, F. X. Meixner, and M. O. Andreae, Biogenic NO emissions from forest and pasture soils: Relating laboratory studies to field measurements, J. Geophys. Res., 107(D20), 8058, doi:10.1029/2001JD000358, 2002.

Veldkamp, E., and Keller, M.: Fertilizer-induced nitric oxide emissions from agricultural soils, Nutrient Cycling in Agroecosystems, 48, 69-77, 1997.

Vinken, G. C. M., Boersma, K. F., Maasakkers, J. D., Adon, M., & Martin, R. V. (2014). Worldwide biogenic soil NO_x emissions inferred from OMI NO_2 observations. Atmospheric Chemistry and Physics, 14(18), 10363–10381. doi:10.5194/acp-14-10363-2014.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Wang, Y., Logan, J. A., and Jacob, D. J.: Global simulation of tropospheric O3-NO x-hydrocarbon chemistry: 2. Model evaluation and global ozone budget, Journal of Geophysical Research: Atmospheres (1984–2012), 103, 10727-10755, 1998.

Wang, Y., McElroy, M. B., Martin, R. V., Streets, D. G., Zhang, Q., and Fu, T. M.: Seasonal variability of NO_x emissions over east China constrained by satellite observations: Implications for combustion and microbial sources, Journal of Geophysical Research: Atmospheres (1984–2012), 112, 2007.

Wang, Y., Zhang, Q. Q., He, K., Zhang, Q., and Chai, L.: Sulfate-nitrate-ammonium aerosols over China: response to 2000–2015 emission changes of sulfur dioxide, nitrogen oxides, and ammonia, Atmos. Chem. Phys., 13, 2635-2652, doi:10.5194/acp-13-2635-2013, 2013.

Williams, E. J., Parrish, D. D., Buhr, M. P., Fehsenfeld, F. C., and Fall, R.: Measurement of soil NO_x emissions in central Pennsylvania, J. Geophys. Res.-Atmos., 93, 9539–9546, doi:10.1029/JD093iD08p09539, 1988.

Williams, E. J., A. Guenther, F. C. Fehsenfeld, An inventory of nitric oxide emissions from soils in the United States, J. Geophys. Res., 97, 7511–7519, 1992.

Yienger, J., and Levy, H.: Empirical model of global soil-biogenic NO~ x emissions, JOURNAL OF GEOPHYSICAL RESEARCH-ALL SERIES-, 100, 11,447-411,447, 1995.

Zhang, W., Mo, J., Yu, G., Fang, Y., Li, D., Lu, X., and Wang, H.: Emissions of nitrous oxide from three tropical forests in Southern China in response to simulated nitrogen deposition, Plant and Soil, 306, 221-236, 2008.

Zhang, Y., Dulière, V., Mote, P.W. and Salathé Jr, E.P.: Evaluation of WRF and HadRM mesoscale climate simulations over the US Pacific Northwest*. Journal of Climate, 22(20), pp.5511-5526, 2009.

Zhang, L., Jacob, D. J., Knipping, E. M., Kumar, N., Munger, J. W., Carouge, C. C., van Donkelaar, A., Wang, Y. X., and Chen, D.: Nitrogen deposition to the United States: distribution, sources, and processes, Atmos. Chem. Phys., 12, 4539–4554, doi:10.5194/acp-12-4539-2012, 2012.

Zhao, C., and Wang, Y.: Assimilated inversion of NO_x emissions over East Asia using OMI NO_2 column measurements, Geophysical Research Letters, 36, 2009.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

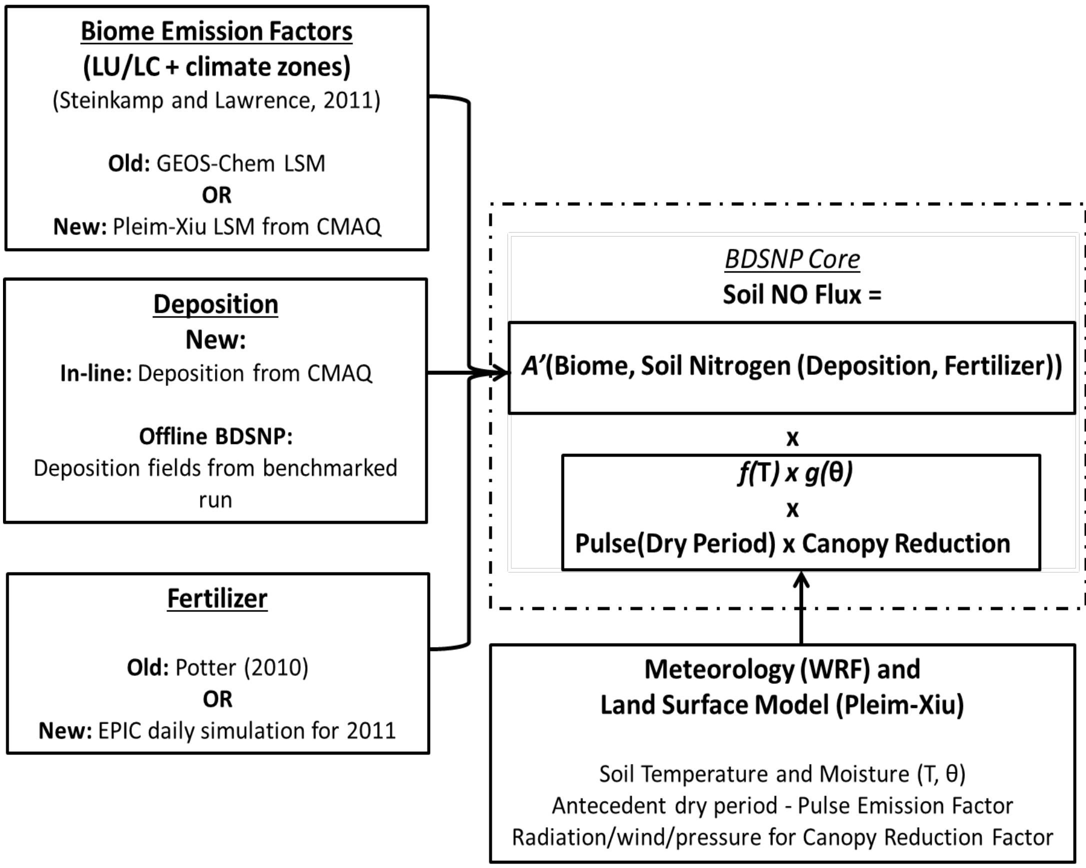


Figure 1 Soil NO emissions modeling framework as implemented offline or in CMAQ (inline). "Old" refers to the Hudman et al. (2012) implementation in GEOS-Chem. "New" refers to our implementation in CMAQ.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

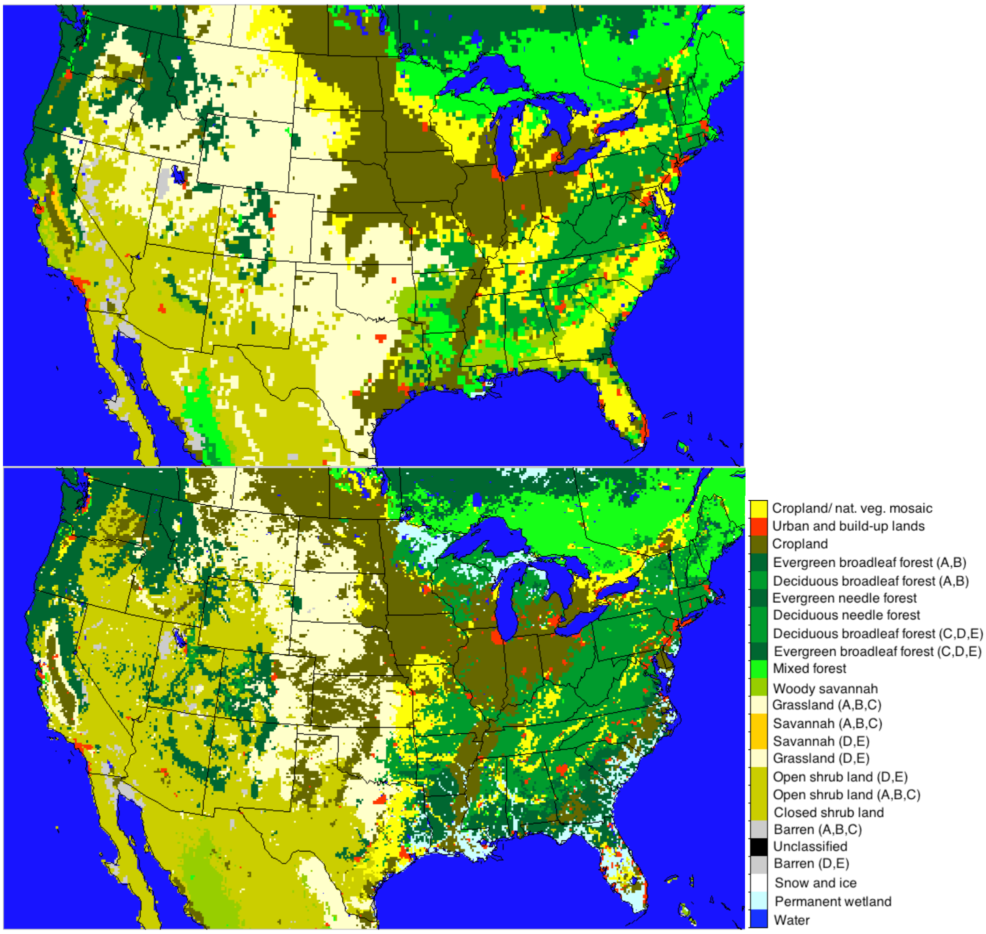
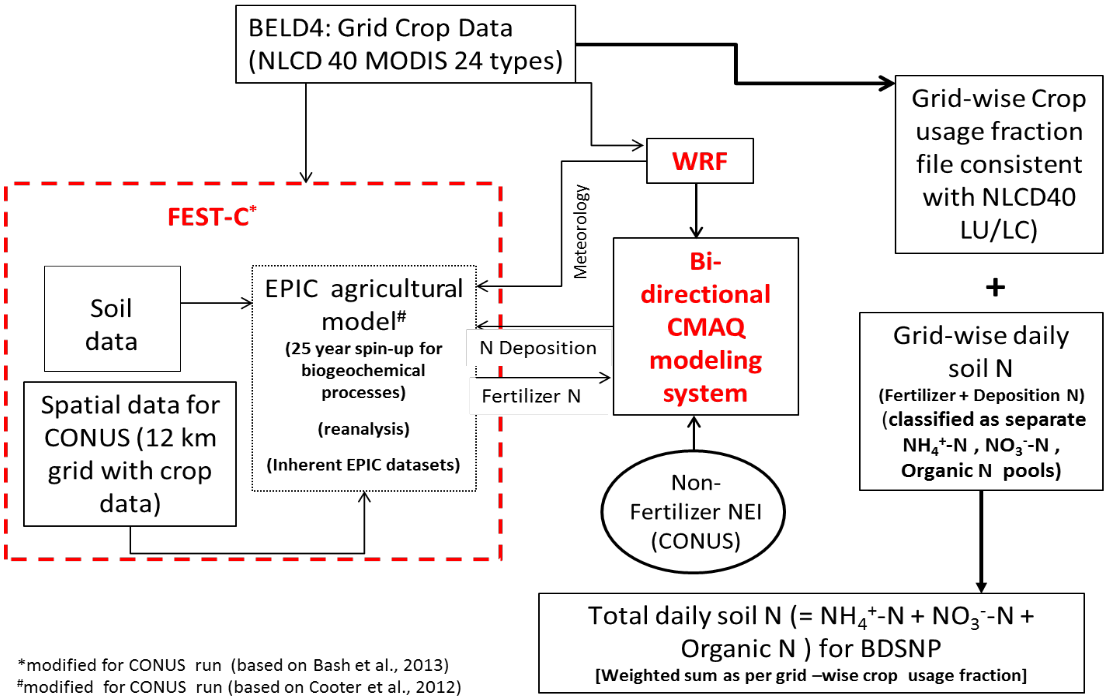


Figure 2 Biomes from GEOS-Chem (0.25° x 0.25°; top) and CMAQ MODIS NLCD40 (12 km x 12 km; bottom) regrouped to match the classifications for which emission factors are available from Steinkamp and Lawrence (2011). See Tables A1 and A2 (right) for the mappings between classifications. The color-bar legends for classifications are as per NLCD definitions (http://www.mrlc.gov/nlcd11_leg.php).



698

699 **Figure 3** Modeling framework for obtaining total soil N from EPIC using FEST-C.

700

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

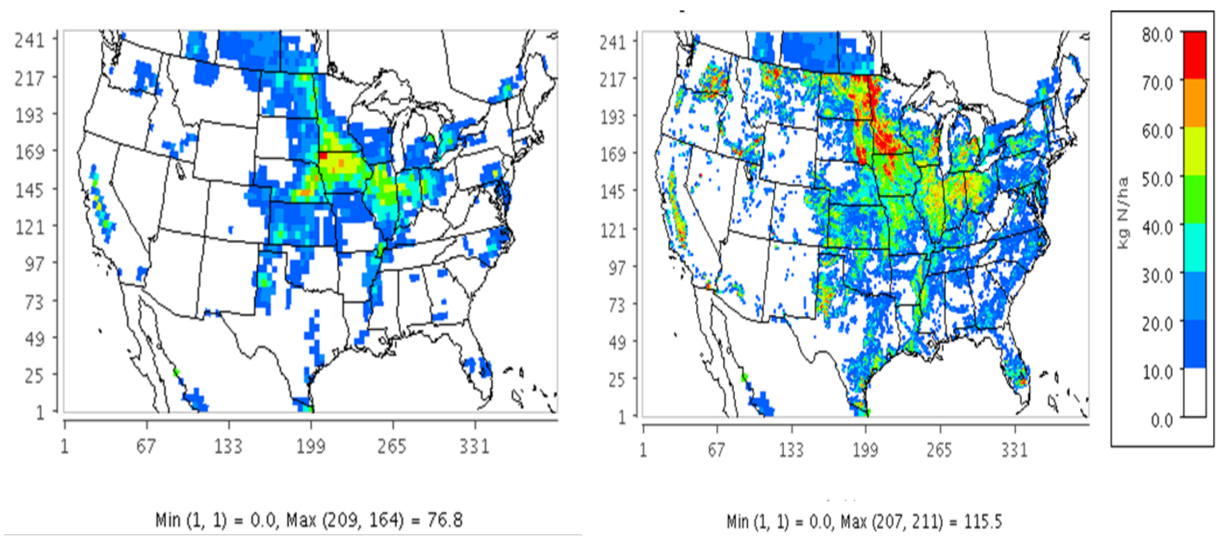


Figure 4 Potter (left) and EPIC (right) annual fertilizer application (Kg N/ha). Since EPIC modeled only the U.S., Potter et al. (2010) is used in both cases to represent Canada and Mexico.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

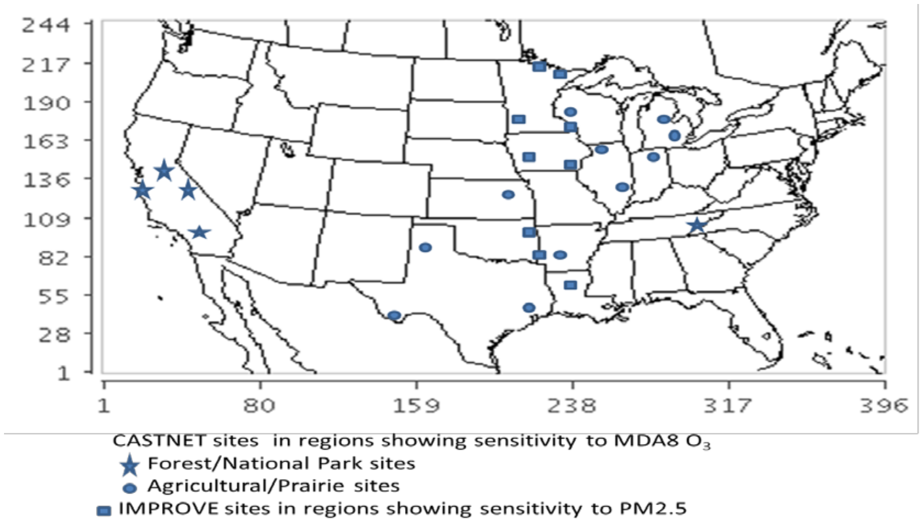
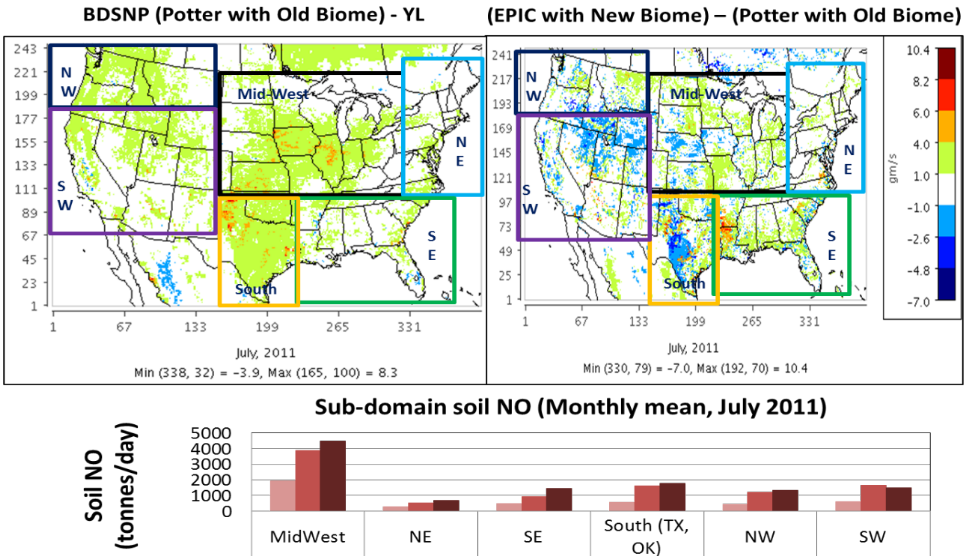


Figure 5 CASTNET (Forest/National Park and agricultural sites) and IMPROVE sites in continental US for comparison of modeled and observed ozone and $PM_{2.5}$.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

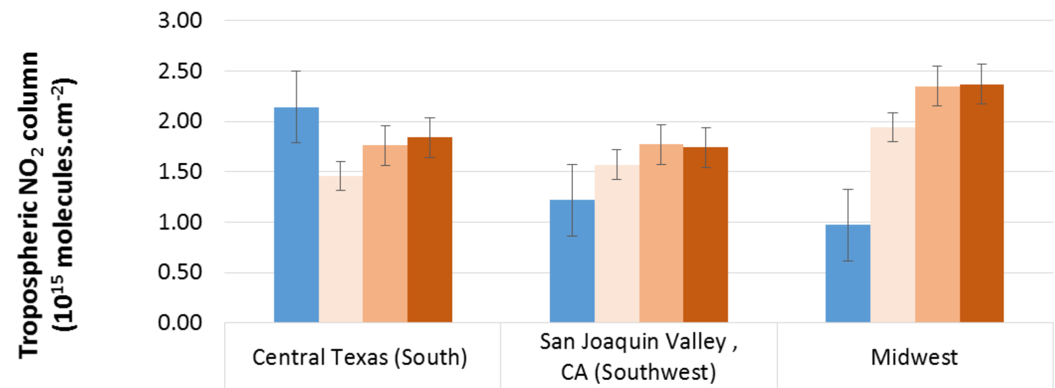
Geoscientific Model Development Discussions



	MidWest	NE	SE	South (TX, OK)	NW	SW
YL	1961	289	496	560	438	594
BDSNP (Potter with Old Biome)	3871	522	916	1633	1227	1668
BDSNP (EPIC with New Biome)	4493	673	1469	1797	1339	1503

Figure 6 Soil NO (tonnes/day) sensitivity to change from YL to BDSNP (Potter and old biome or 'old') (left) and to the fertilizer and biome scheme within BDSNP (right) over sub-domains (boxes).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016



	Central Texas (South)	San Joaquin Valley , CA (Southwest)	Midwest
OMI	2.14	1.22	0.97
YL	1.46	1.57	1.94
BDSNP (Potter with old biome)	1.76	1.77	2.35
BDSNP (EPIC with new biome)	1.84	1.74	2.37

Figure 7 Spatial average for Tropospheric NO_2 (molecules cm^{-2}) over regions with high soil NO sensitivity with switch from YL to BDSNP (as in Figure 6) with comparison to OMI NO_2. NO_2 column are temporal average for July 2011 at OMI overpass time.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

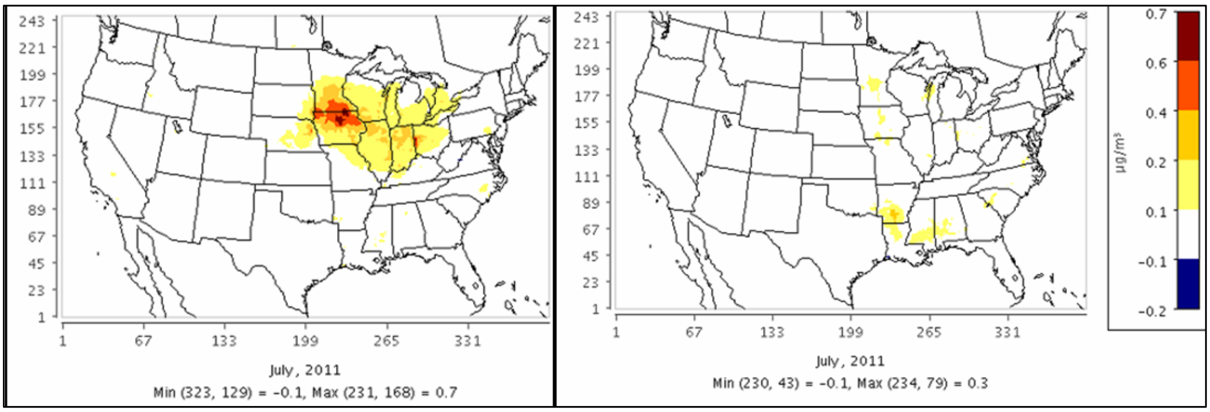


Figure 8 Changes in modeled daily average $PM_{2.5}$ when switching from: a) YL to BDSNP (Potter fertilizer data with original biome map) (left) and b) BDSNP (Potter with original biomes) to BDSNP (EPIC with new biomes) (right).

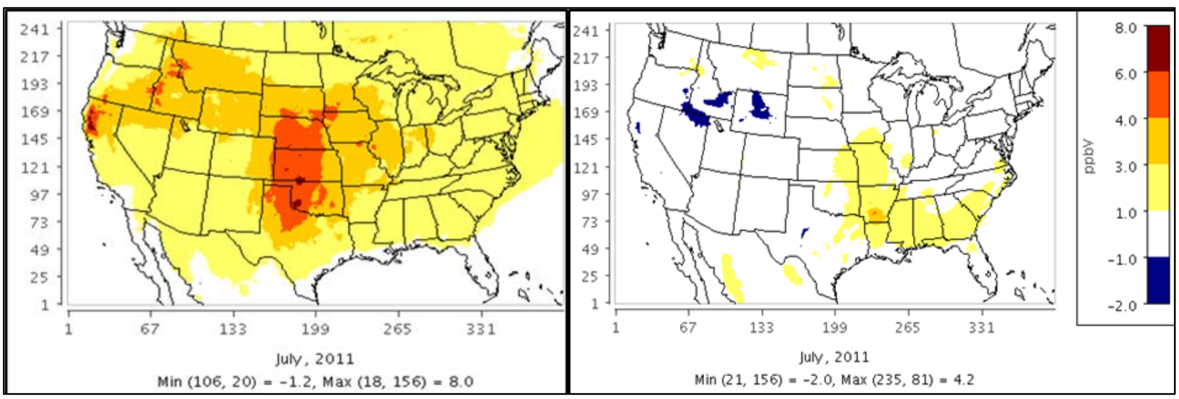


Figure 9 Changes in modeled maximum daily 8-hour ozone (MDA8) when switching from: a) YL to BDSNP (Potter fertilizer data with original biome map) (left) and b) BDSNP (Potter with original biomes) to BDSNP (EPIC with new biomes) (right).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

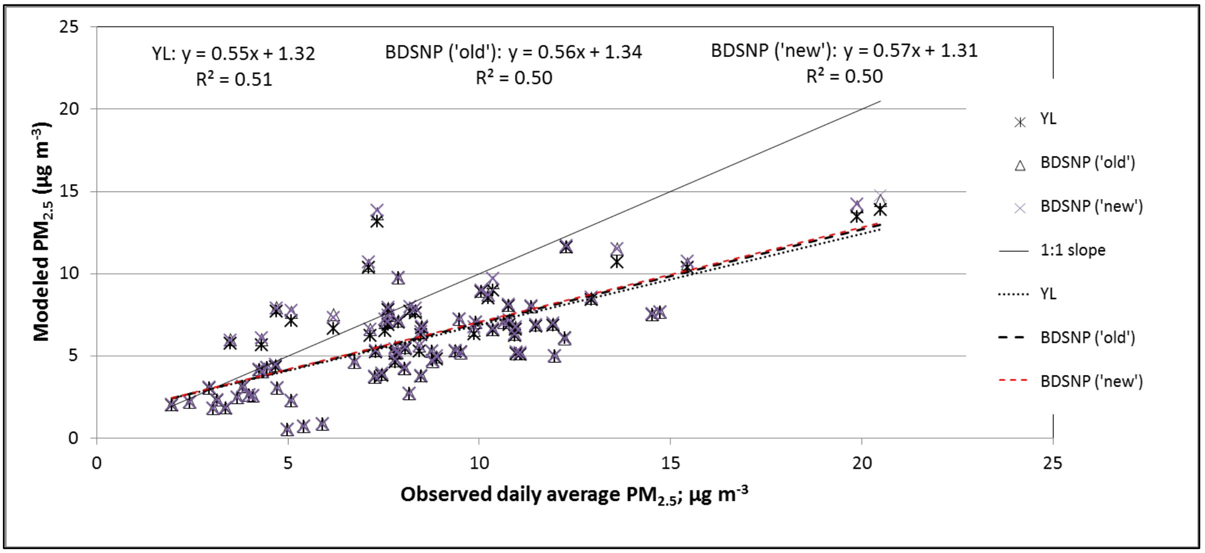
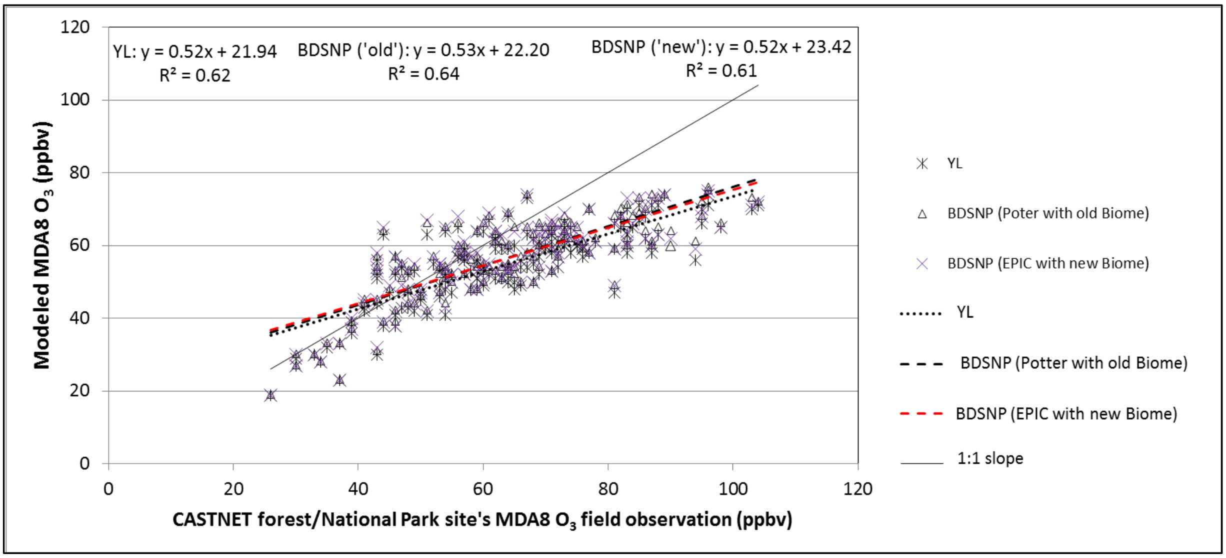


Figure 10 Comparison of the three inline BDSNP-CMAQ cases with IMPROVE $PM_{2.5}$ data (Malm et al., 1994) in continental US for Daily Average $PM_{2.5}$ for July 2011.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development
Discussions
Open Access



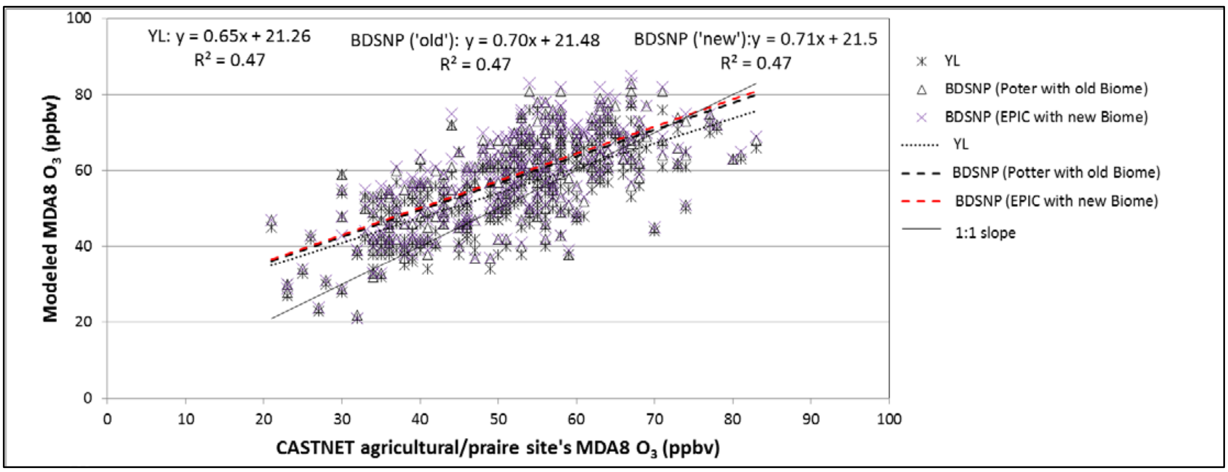


Figure 11 Comparison of the three inline BDSNP-CMAQ cases with CASTNET MDA8 O_3 data for forest/National Park sites in California (top, number of evaluation sites, n=147) and agricultural/prairie sites in mid-west and south US (bottom, n=311) for July 2011.

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

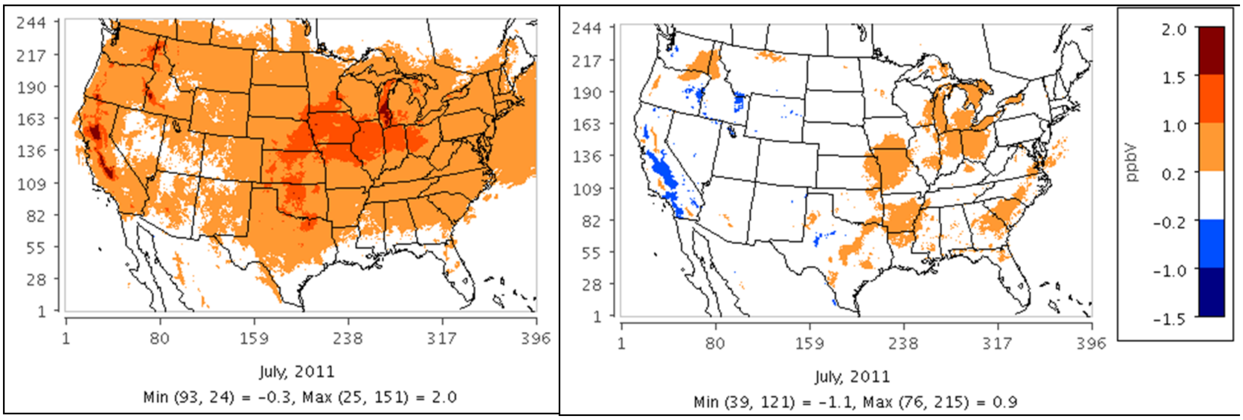


Figure 12 Difference in monthly mean MDA8 O_3 perturbation between: a) BDSNP ('old') – YL (left) and, b) BDSNP ('new') – BDSNP ('old') (right). MDA8 O_3 perturbations are from perturbed anthropogenic NO_x estimates 2011 base case to 2025 base case, BAU (US EPA, 2015).

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Table 1 Modeling configuration used for the WRF-BDSNP-CMAQ CONUS domain runs.

WRF/MCIP			
Version:	ARW V3.6.1	**Shortwave radiation:**	RRTMG scheme
Horizontal resolution:	CONUS (12kmX12km)	**Surface layer physic:**	Pleim-Xiu surface model
Vertical resolution:	26 layer	**PBL scheme:**	ACM2
Boundary condition:	NARR 32km	**Microphysics:**	Morrison double-moment scheme
Initial condition:	NCEP-ADP	**Cumulus parameterization:**	Kain-Fritsch scheme
Longwave radiation:	RRTMG scheme	**Assimilation:**	Analysis nudging above PBL for temperature, moisture and wind speed
BDSNP			
Horizontal resolution:	Same as WRF/MCIP	**Emission factor:**	Steinkamp and Lawrence (2011)
Soil Biome type:	24 types based on NLCD40 (new) 24 types based on GEOS-Chem LSM (old)	**Fertilizer database:**	EPIC 2011 based from FEST-C (new) Potter et al. (2010) (old)
CMAQ			
Version:	V5.02	**Anthropogenic emission:**	NEI2011
Horizontal resolution:	Same as WRF/MCIP	**Biogenic emission:**	BEIS V3.1 in-line
Initial condition:	Pleim-Xiu (new) GEOS-Chem (old)	**Boundary condition:**	Pleim-Xiu (new) GEOS-Chem (old)
Aerosol module:	AE5	**Gas-phase mechanism:**	CB-05
Simulation Case Arrangement (in-line with CMAQ)			
1. YL:	WRF/MCIP-CMAQ with standard YL soil NO scheme		
2. BDSNP (Potter with old Biome or 'old'):	WRF/MCIP-BDSNP-CMAQ with Potter and old biome		
3. BDSNP (EPIC with new Biome or 'new'):	WRF/MCIP-BDSNP-CMAQ with EPIC and new biome		
Simulation Time Period			
	July 1-31, 2011 for CMAQ simulation with **in-line soil NO BDSNP module** Daily simulations in Year 2011 for **standalone BDSNP** soil NO BDSNP module (July 1-31, 2011 for sensitivity analysis)		
Model Performance Evaluation			
USEPA Clean Air Status and Trends Network (CASTNET) data for MDA8 ozone Interagency Monitoring of Protected Visual Environments (IMPROVE) Network (Malm et al., 1994) for $PM_{2.5}$ OMI NO_2 satellite retrieval product as derived in Lamsal et al., 2014 for NO_2 column			

Geoscientific Model Development Discussions

Table 2 Aggregated performance statistics of CMAQ modeled daily average $PM_{2.5}$ for stations showing sensitivities with change in soil NO between YL scheme and our 2 inline BDSNP implementations ('old' and 'new') for CONUS in July 2011 as compared to observations at these sites

	Metrics				
Daily average $PM_{2.5}$ July (1 July- 31 July), 2011	Sample Size			81	
	Mean observed ($\mu g/m^3$)			8.26	
	3 CMAQ inline cases		YL	BDSNP (Potter with old biome)	BDSNP (EPIC with new biome)
	Mean predicted ($\mu g/m^3$)		5.91	6.04	6.08
	MAGE (Mean Absolute Gross error)		2.86	2.80	2.77
	RMSE		3.45	3.40	3.38
	R (correlation coefficient)	Pearson's	0.72	0.71	0.71
		Spearman's Ranked	0.65	0.63	0.63
	NMB (%)		-28.52	-26.90	-26.44
	NME (%)		34.64	33.88	33.57

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development
Discussions
Open Access

Table 3 Performance statistics of CMAQ modeled MDA8 Ozone for 16 CASTNET remote sites grouped into two categories: a) 11 sites with moist or wet soil condition (monthly mean soil moisture (m^3/m^3), $\theta_{mean} > 0.175$), and b) 5 sites with dry soil condition ($\theta_{mean} < 0.175$) , using soil NO from YL and our two inline BDSNP schemes.

July 2011	Metrics				
11 CASTNET sites (mostly agricultural/ prairie sites, Mostly wet soil conditions)	Sample size		311		
	Mean observed (ppbv)		51.76		
	3 CMAQ inline cases		YL	BDSNP (Potter with old biome)	BDSNP (EPIC with new biome)
	Mean modeled (ppbv)		55.25	57.93	58.60
	M_{AGE} (Mean Absolute Gross error)		7.78	9.16	9.65
	RMSE		9.41	10.96	11.47
	R (correlation coefficient)	Pearson's	0.50	0.51	0.50
		Spearman's Ranked	0.46	0.49	0.48
	NMB (%)		7.57	12.80	14.08
	NME (%)		15.65	18.38	19.33
5 CASTNET sites (mostly forest/National Park sites near San Joaquin valley CA, Dry soil conditions)	Sample size		147		
	Mean observed (ppbv)		64.38		
	Mean modeled (ppbv)		55.17	57.01	56.87
	M_{AGE} (Mean Absolute Gross error)		11.41	10.13	10.44
	RMSE		13.13	11.80	12.12
	R (correlation coefficient)	Pearson's	0.71	0.72	0.72
		Spearman's Ranked	0.68	0.69	0.69
	NMB (%)		-13.14	-10.23	-10.35
	NME (%)		16.95	15.04	15.45

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

Table 4 Emission perturbation factors applied to anthropogenic NO_x emissions for each sector listed in NEI as per EPA's RIA base-line reductions from 2011 to 2025 with BAU (Table 2A-1, https://www3.epa.gov/ttn/ecas/docs/20151001ria.pdf)

Sectors (NEI file names)	Perturbation factor
Electric Generating Unit(EGU)-point (ptimp- ptegu, ptegu_pk)	0.7
NonEGU-point (ptnonipm)	1
Point oil and gas (pt_oilgas)	0.92
Nonpoint oil and gas (np_oilgas)	1.108
Wild and Prescribed Fires (ptwildfire, ptprescfire)	1
Residential wood combustion (rwc)	1.029
Other nonpoint (nonpt)	1.039
Onroad (onroad)	0.298
Nonroad mobile equipment sources (nonroad)	0.5
Category 3 Commercial marine vessel (c3marine)	0.77
Locomotive and Category 1/Category 2 Commercial marine vessel (c1c2rail)	0.62

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access
EGU

Appendix

Table A1 List of 24 soil biome emission factor (EF) from Steinkamp and Lawrence (2010)

ID	**MODIS land cover**	**Köppen main climate[(1)]**	**EF1 (world geometric mean)**	**EF2 (world arithmetic mean)**	**EF3 (North American)**
1	Water	--	0	0	0
2	Permanent wetland	--	0	0	0
3	Snow and ice	--	0	0	0
4	Barren	D,E	0	0	0
5	Unclassified	--	0	0	0
6	Barren	A,B,C	0.06	0.06	0.06
7	Closed shrub land	--	0.09	0.21	0.05
8	Open shrub land	A,B,C	0.09	0.21	0.09
9	Open shrub land	D,E	0.01	0.01	0.01
10	Grassland	D,E	0.84	1.05	0.62
11	Savannah	D,E	0.84	1.05	0.84
12	Savannah	A,B,C	0.24	0.97	0.24
13	Grassland	A,B,C	0.42	1.78	0.37
14	Woody savannah	--	0.62	0.74	0.62
15	Mixed forest	--	0.03	0.14	0.00
16	Evergreen broadleaf forest	C,D,E	0.36	0.95	0.36
17	Deciduous broadleaf forest	C,D,E	0.36	0.95	0.61
18	Deciduous needle. forest	--	0.35	0.95	0.35
19	Evergreen needle. forest	--	1.66	4.60	1.66
20	Deciduous. broadl. forest	A,B	0.08	0.13	0.08
21	Evergreen broadl. forest	A,B	0.44	1.14	0.44
22	Cropland	--	0.57	3.13	0.33
23	Urban and build-up lands	--	0.57	3.13	0.57
24	Cropland/nat. veg. mosaic	--	0.57	3.14	0.57

(1). A-equatorial, B-arid, C-warm temperature, D-snow, E-polar (see Figure 2 for spatial map)

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions
Open Access

Table A2 Mapping table to create the 'new' soil biome map based on NLCD40 MODIS land cover categories

ID	NLCD40 MODIS CATEGORY (40)	ID	SOIL BIOME CATEGORY (24)
1	Evergreen Needle leaf Forest	19	Evergreen Needle leaf Forest
2	Evergreen Broadleaf Forest	16 and 21	Evergreen Broadleaf Forest
3	Deciduous Needle leaf Forest	18	Dec. Needle leaf Forest
4	Deciduous Broadleaf Forest	17 and 20	Dec. Broadleaf Forest
5	Mixed Forests	15	Mixed Forest
6	Closed shrublands	7	Closed shrublands
7	Open shrublands	8 and 9	Open srublands
8	Woody Savannas	14	Woody savannah
9	Savannas	11 and 12	Savannah
10	Grasslands	10 and 13	Grassland
11	Permanent Wetlands	2	Permanent Wetland
12	Croplands	22	Cropland
13	Urban and Built Up	23	Urban and build-up lands
14	Cropland-Natural Vegetation Mosaic	24	Cropland/nat. veg. mosaic
15	Permanent Snow and Ice	3	Snow and ice
16	Barren or Sparsely Vegetated	6	Barren
17	IGBP Water	1	Water
18	Unclassified	1	Water
19	Fill value	1	Water
20	Open Water	1	Water
21	Perennial Ice-Snow	3	Snow and ice
22	Developed Open Space	23	Urban and build-up lands
23	Developed Low Intensity	23	Urban and build-up lands
24	Developed Medium Intensity	23	Urban and build-up lands
25	Developed High Intensity	23	Urban and build-up lands
26	Barren Land (Rock-Sand-Clay)	24	Cropland/nat. veg. mosaic
27	Unconsolidated Shore	24	Cropland/nat. veg. mosaic
28	Deciduous Forest	16 and 21	Evergreen Broadleaf Forest
29	Evergreen Forest	19	Evergreen Needle leaf Forest
30	Mixed Forest	15	Mixed Forest
31	Dwarf Scrub	8 and 9	Open shrublands
32	Shrub-Scrub	8 and 9	Open shrubland
33	Grassland-Herbaceous	10 and 13	Grassland
34	Sedge-Herbaceous	14	Woody savannah
35	Lichens	10 and 13	Grassland
36	Moss	10 and 13	Grassland
37	Pasture-Hay	24	Cropland/nat. veg. mosaic
38	Cultivated Crops	22	Cropland
39	Woody Wetlands	2	Permanent Wetland
40	Emergent Herbaceous Wetlands	2	Permanent Wetland

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

Geoscientific Model Development Discussions

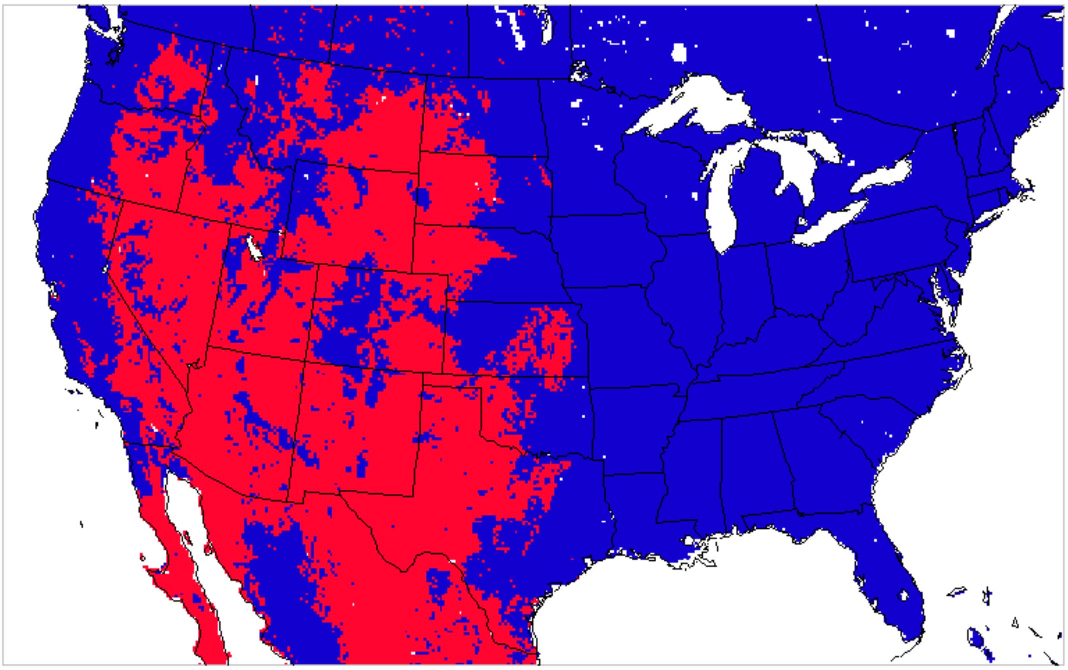


Figure B1 Arid (red) and non-arid (blue) region over Continental US (12km resolution)

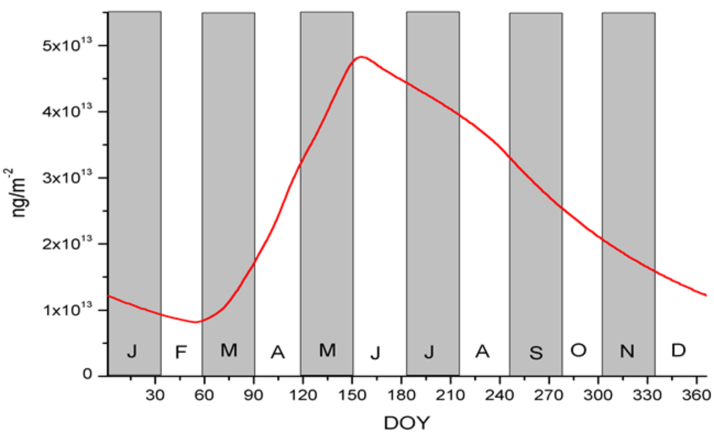


Figure B2 Daily variation of total N from fertilizer application (from Potter et al. (2010)) processed from BDSNP to establish timing over continental US throughout 2011

Geosci. Model Dev. Discuss., doi:10.5194/gmd-2016-123, 2016
Manuscript under review for journal Geosci. Model Dev.
Published: 2 June 2016

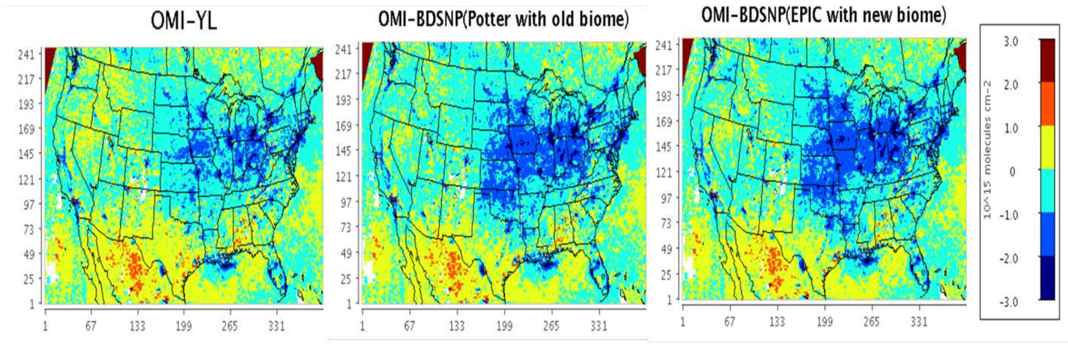


Figure B3 Difference of OMI NO_2 column with NO_2 column simulated from the three inline CMAQ cases: YL, BDSNP (Potter with old biome), BDSNP (EPIC with new Biome) (left to right) over OMI overpass time averaged for July 2011 over CONUS. Note: In contour plots, white refers to gaps/no-fill values in OMI product and dark red at upper corners are due to gaps in CMAQ NO_2 column after temporal averaging at OMI overpass time.