

# Earth's Future

## RESEARCH ARTICLE

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### Key Points:

- Direct nitrous oxide ( $\text{N}_2\text{O}$ ) emission from N inputs of fertilizers and residues ranged from 3,830 to 7,875 ton  $\text{N yr}^{-1}$  from 2000 to 2015 in California cropland
- Simulated annual direct  $\text{N}_2\text{O}$  emission decreased by 47% from 2000 to 2015, primarily driven by changes in land use and farming management
- Coupling model with environmental and activity database improved characterization of direct  $\text{N}_2\text{O}$  emissions from California cropland

### Supporting Information:

Supporting Information may be found in the online version of this article.

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## A Decreasing Trend of Nitrous Oxide Emissions From California Cropland From 2000 to 2015

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**Abstract** Mitigation of greenhouse gas emissions from agriculture requires an understanding of spatial-temporal dynamics of nitrous oxide ( $\text{N}_2\text{O}$ ) emissions. Process-based models can quantify  $\text{N}_2\text{O}$  emissions from agricultural soils but have rarely been applied to regions with highly diverse agriculture. In this study, a process-based biogeochemical model, DeNitrification-DeComposition (DNDC), was applied to quantify spatial-temporal dynamics of direct  $\text{N}_2\text{O}$  emissions from California cropland employing a wide range of cropping systems. DNDC simulated direct  $\text{N}_2\text{O}$  emissions from nitrogen (N) inputs through applications of synthetic fertilizers and crop residues during 2000–2015 by linking the model with a spatial-temporal differentiated database containing data on weather, crop areas, soil properties, and management. Simulated direct  $\text{N}_2\text{O}$  emissions ranged from 3,830 to 7,875 tonnes  $\text{N}_2\text{O-N yr}^{-1}$ , representing 0.73%–1.21% of the N inputs.  $\text{N}_2\text{O}$  emission rates were higher for hay and field crops and lower for orchard and vineyard. State cropland total  $\text{N}_2\text{O}$  emissions showed a decreasing trend primarily driven by reductions of cropland area and N inputs, the trend toward growing more orchard, and changes in irrigation. Annual direct  $\text{N}_2\text{O}$  emissions declined by 47% from 2000 to 2015. Simulations showed  $\text{N}_2\text{O}$  emission variations could be explained not only by cropland area and N fertilizer inputs but also climate, soil properties, and management besides N fertilization. The detailed spatial-temporal emission dynamics and driving factors provide knowledge toward effective  $\text{N}_2\text{O}$  mitigation and highlight the importance of coupling process-based models with high-resolution data for characterizing the spatial-temporal variability of  $\text{N}_2\text{O}$  emissions in regions with diverse croplands.

**Plain Language Summary** Nitrous oxide ( $\text{N}_2\text{O}$ ) is the third most important greenhouse gas and an important ozone-depleting substance. It is challenging to quantify  $\text{N}_2\text{O}$  emissions from croplands in regions with highly diverse agriculture. In this study, a process-based biogeochemical model, DeNitrification-DeComposition (DNDC), was applied to quantify spatial-temporal dynamics of direct  $\text{N}_2\text{O}$  emissions from California cropland, which has a wide range of cropping systems. DNDC simulated direct  $\text{N}_2\text{O}$  emissions from nitrogen (N) inputs from synthetic fertilizers and crop residues during 2000–2015. Simulated direct  $\text{N}_2\text{O}$  emissions ranged from 3,830 to 7,875 tonnes  $\text{N yr}^{-1}$ , representing 0.73%–1.21% of the N inputs from synthetic fertilizers and crop residues. Simulated annual direct  $\text{N}_2\text{O}$  emissions from California cropland declined by 47% from 2000 to 2015. This decreasing trend could be explained by reductions of cropland area and associated N inputs, the trend toward growing more orchard crops, and changes in irrigation. This study characterized spatial-temporal dynamics of  $\text{N}_2\text{O}$  emissions from California cropland, and provided knowledge toward effective  $\text{N}_2\text{O}$  mitigation. It also highlights the importance of coupling process-based models with high-resolution data to quantify the spatial-temporal variability of  $\text{N}_2\text{O}$  emissions in regions with complicated agricultural systems.

## 1. Introduction

Nitrous oxide ( $\text{N}_2\text{O}$ ) is the third most important greenhouse gas (GHG) and an important ozone-depleting substance emitted through human activities (Ravishankara et al., 2009; Stocker et al., 2014). The concentration of atmospheric  $\text{N}_2\text{O}$  has risen continually since the late 1970s and the  $\text{N}_2\text{O}$  increase has been accelerating since 2009, primarily due to accelerated  $\text{N}_2\text{O}$  emissions from agricultural soils (Stocker et al., 2014; Thompson et al., 2019). Globally, agricultural sources of  $\text{N}_2\text{O}$  emissions are approximately 4.1 Tg ( $10^{12}$  g)  $\text{N-N}_2\text{O yr}^{-1}$  (Stocker et al., 2014; Syakila and Kroeze, 2011), primarily due to enrichment of reactive nitrogen (N) in the agricultural environment (Davidson, 2009).

Nitrous oxide emissions from agricultural soils are predominately of microbial origin and are extremely variable in both time and space (e.g., Bouwman et al., 2002) due to high variability in vegetation cover, environmental factors (e.g., inorganic N substrates, dissolvable organic carbon availability, temperature, oxygen status, and pH), and farming management practices (FMPs) that regulate N<sub>2</sub>O emissions (Butterbach-Bahl et al., 2013; Robertson and Groffman, 2007). It is challenging to quantify N<sub>2</sub>O emissions, especially at large regional or national scales, due to high temporal and spatial variability of N<sub>2</sub>O emissions (Leip et al., 2018). Process-based models, such as the DeNitrification-DeComposition (DNDC) model, take into account both environmental factors and FMPs that regulate N<sub>2</sub>O emissions from soils, and therefore provide an effective method for quantifying N<sub>2</sub>O emissions and developing management for N<sub>2</sub>O mitigation in agricultural systems (Butterbach-Bahl et al., 2013; Giltrap et al., 2010). However, these models have rarely been applied to quantify N<sub>2</sub>O emissions from regions with diverse agriculture because the models have usually been verified against limited type of cropping systems (Giltrap et al., 2010; Smith, 2017). In addition, limited availability of spatiotemporally differentiated driver data (e.g., weather, soil, FMPs) constrains the applicability of models for diverse agricultural ecosystems.

To meet ambitious climate targets, N<sub>2</sub>O emission will need to decrease (Masson-Delmotte et al., 2018). Mitigation of N<sub>2</sub>O emission, however, could be hindered by uncertainty in its spatial-temporal emission dynamics. In this study, we applied the DNDC model to quantify multiyear N<sub>2</sub>O emissions from California cropland to address the uncertainty in quantifying N<sub>2</sub>O emissions from diverse cropping systems. California is one of the most important and diverse agricultural producers among U.S. states, with over 400 commodities (CDFA, 2012) and the highest crop cash receipts in the United States (CDFA, 2018). A number of field-scale measurements have been performed to quantify GHG emissions and assess GHG mitigation strategies in California cropping systems in recent years (e.g., Burger and Horwath, 2012; Garland et al., 2014; Kennedy et al., 2013; Lazcano et al., 2016; Pittelkow et al., 2013; Smart et al., 2011). The field-scale measurements characterized the N<sub>2</sub>O emission rates that had a high level temporal and spatial variability, indicating complex regulation of emissions by environmental variables and management activities (Verhoeven et al., 2017). The large temporal and spatial variability of N<sub>2</sub>O emissions along with the diverse cropping systems and FMPs make the quantification of N<sub>2</sub>O emissions particularly challenging in California.

Recently, DNDC has been evaluated against field measurements of N<sub>2</sub>O emissions and been applied to assess the influences of irrigation management practices on N<sub>2</sub>O emissions from California cropland using a database with input data in 2002 (Deng et al., 2018a, 2018b). However, spatial-temporal dynamics of N<sub>2</sub>O emissions from California cropland have not been well characterized. In this study, we applied the DNDC model to quantify the direct N<sub>2</sub>O emissions from California cropland during 2000–2015 by linking the model with a spatial-temporal differentiated database containing multiyear input data from 2000 to 2015 on weather, crop types and areas, soil properties, and FMPs. We simulated direct N<sub>2</sub>O emissions from California cropland encompassing highly diversified cropping systems, with the objectives of evaluating the long-term trend and spatial variations of N<sub>2</sub>O emissions from California cropland and identifying possible drivers of the trends.

## 2. Materials and Methods

### 2.1. The DNDC Model

The DNDC model (Li et al., 1992a, 1992b) used in this study was originally developed for quantifying carbon (C) sequestration and GHG emissions from agroecosystems, and has been extensively applied to simulate N<sub>2</sub>O emissions from different types of ecosystems (Deng et al., 2020; Gilhespy et al., 2014; Giltrap et al., 2010). The model simulates soil C and N transformations through a series of biogeochemical reactions, such as decomposition, microbial assimilation, plant uptake, ammonium adsorption, ammonia volatilization, nitrification, denitrification, and nitrate leaching. The DNDC model has also incorporated a relatively complete suite of FMPs (e.g., tillage, fertilization, manure amendment, return of crop residues, irrigation, and cultivation of cover crops) to simulate impacts of FMPs on soil environmental conditions and transformations of C and N. The FMPs incorporated in DNDC have enabled the model to simulate GHG emissions from regions with different cropping systems and agricultural management practices. An extended model description is in Supporting Information S1.

DNDC simulations of N<sub>2</sub>O emissions from California cropland have been evaluated against field measurements of N<sub>2</sub>O emissions from typical cropping systems in California (Deng et al., 2018b). The field data covered major crop categories including the following: hay, field crops, vegetable, orchard, and vineyard, and represented a wide

range of climate and soil conditions and FMPs in California agriculture. DNDC reliably predicted seasonal or annual total  $N_2O$  emissions for the cropping systems. The predicted  $N_2O$  emissions were significantly correlated with the corresponding measurements ( $R^2 = 0.87$ ,  $P < 0.001$ ) and the slope of the zero-intercept linear regression between the simulations and measurements was 1.0 (Figure S1 in Supporting Information S1).

## 2.2. Database Construction

A spatial-temporal differentiated database was constructed to drive the DNDC model to simulate direct  $N_2O$  emissions from California cropland. The database included input information of daily meteorological data, land area of different crop types (in total 54 types), soil properties, and FMPs for each crop type. The basic unit for organizing the database was “county” because reliable data of land area for different crop types were available at the county scale. In each of California's 58 counties, input information was collected and organized into the database to support simulations.

Sources for most information and parameter values in the database are provided in detail in Deng et al. (2018a). In general, daily meteorological data from 1998 to 2015 were derived from weather data produced by the DAYMET model (Thornton et al., 2016) to support the simulations from 2000 to 2015 (Figure S2 in Supporting Information S1). DAYMET climate data are available at 1-km<sup>2</sup> resolution for the United States, and we chose the data from the 1-km<sup>2</sup> cell that was closest to the area-weighted geographical center of cropland in each county. Soil property data, including bulk density, clay content, organic carbon content, and pH, required by DNDC for regional simulations were determined based on the Soil Survey Geographic (SSURGO) database developed by the Natural Resource Conservation Service (NRCS), United States Department of Agriculture (USDA; NRCS, 2016). We estimated the area-weighted means of the soil properties for croplands in each county (Deng et al., 2018a), and used the area-weighted means as “representative” soil input parameters for simulating “representative”  $N_2O$  emissions from California cropland. In addition, the minimum and maximum values of soil properties were determined for each county to support the “most sensitive factor” method (Li, 2007; Li et al., 2004, 2005) for quantifying uncertainties of  $N_2O$  emissions resulting from soil variability, which is often a major source of uncertainty when applying models to quantify cropland  $N_2O$  emissions at regional scales (Butterbach-Bahl et al., 2004; Li et al., 2004). The “most sensitive factor” method quantifies uncertainties based on simulations using the minimum and maximum values of the most sensitive factor for a concerned output ( $N_2O$  emission in this study; Li, 2007; Li et al., 2004, 2005). The simulations produce two  $N_2O$  emission values that are corresponding to the minimum and maximum values of the most sensitive factor, and the range formed by the two values is assumed as the uncertainties (Li, 2007; Li et al., 2004, 2005). In this study, the SOC content was identified as the most sensitive factor for simulated direct  $N_2O$  emissions from California cropland through a sensitivity analysis (Supporting Information S1). The crop parameters related to simulations of crop growth were determined by referring to on-site studies (Deng et al., 2018b), crop yields from the Cost and Return studies for California crop commodities by the University of California, Davis (UCD, 2016), or using model defaults that were derived from a large collection of literature values. Typical FMPs for each of the 54 crops were developed from open literature and surveys, including the Cost and Return studies for crop commodities (UCD, 2016), the Statewide Irrigation Methods Surveys conducted by the California Department of Water Resource (CDWR, 2016; Orang et al., 2008; Tindula et al., 2013), N fertilizer use analyses by Rosenstock et al. (2013), and the Census of Agriculture (USDA, 2004, 2009, 2014). We compiled crop specific management practices, including planting and harvest dates, tillage, fertilization, irrigation, rice-paddy flooding, and residue management, for each of the 54 crops.

Because we did not detect inter annual changes for most of FMPs from 2000 to 2015 from the sources for developing FMPs, we used the same set of input parameters for these FMPs (i.e., planting and harvest dates, tillage, fertilization, rice-paddy flooding, and residue management) for all years, except for irrigation. For most crop types in California, there are four major irrigation management practices: Surface gravity, sprinkler, drip, and subsurface drip (CDWR, 2016). Since the early 1990s, irrigation management in California has undergone changes, with an increase in low-volume (drip and subsurface drip) irrigation, and a decrease in high-volume surface gravity irrigation in all tracked crop categories, including hay, field crops, vegetable, melon, and berries (VMB), orchards, and vineyards (Figure S3 in Supporting Information S1; Orang et al., 2008; Tindula et al., 2013). We therefore performed four  $N_2O$  simulations corresponding to these irrigation methods for each crop type, and used the simulations and fraction of different irrigation methods from 2000 to 2015 to calculate direct  $N_2O$  emissions

**Table 1**  
*State Total Cropland Area Used for Simulating the Direct Nitrous Oxide Emissions, N Inputs From Synthetic Fertilizers and Crop Residue Return, Disaggregated by Crop Categories*

Category	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
<b>Cropland area (1000 ha)</b>																
Hay	1226	1238	1325	1225	1172	1139	1112	1022	1019	952	905	829	835	802	761	681
Field crops	1031	941	906	910	939	845	767	802	811	724	778	887	837	752	566	507
VMB	482	466	491	472	471	471	464	451	439	436	439	437	443	442	446	438
Orchard	600	609	642	617	606	616	623	642	656	677	691	724	736	758	775	793
Vineyard	326	332	333	322	224	314	311	308	306	307	309	309	309	315	332	328
Total	3,664	3,587	3,696	3,547	3,412	3,385	3,277	3,224	3,230	3,096	3,122	3,185	3,160	3,070	2880	2747
<b>N inputs from synthetic fertilizers (<math>10^6</math> kg N yr<sup>-1</sup>)</b>																
Hay	101.9	104.4	108.7	100.5	97.3	95.3	91.4	86.4	84.3	78.6	76.0	70.2	71.5	66.1	61.9	54.1
Field crops	205.4	186.4	180.7	185.4	188.0	170.2	152.2	164.1	172.0	150.4	160.3	184.2	175.3	153.2	113.9	100.9
VMB	100.5	98.2	103.5	99.8	99.1	99.8	98.3	94.7	92.6	91.8	92.7	92.2	93.9	93.3	94.3	92.5
Orchard	108.2	110.7	117.1	113.6	112.1	114.7	116.9	121.2	124.3	129.0	132.0	139.2	142.9	146.9	150.9	154.8
Vineyard	14.7	15.0	15.0	14.5	10.1	14.1	14.0	13.9	13.8	13.8	13.9	13.9	13.9	14.2	14.9	14.8
Total	530.6	514.7	524.9	513.7	506.6	494.1	472.6	480.2	487.0	463.6	474.8	499.6	497.4	473.6	436.0	417.1
<b>N inputs from crop residues (<math>10^6</math> kg N yr<sup>-1</sup>)</b>																
Hay	59.8	57.9	64.9	63.6	56.0	61.8	60.6	53.7	55.8	53.5	52.2	45.6	46.6	46.2	47.2	42.6
Field crops	26.6	23.9	22.3	22.1	22.2	20.8	18.3	19.9	19.4	16.3	20.8	22.5	21.0	19.3	13.8	11.5
VMB	21.6	20.9	21.3	21.5	21.7	22.1	21.5	19.5	18.9	19.3	19.0	18.9	18.2	18.7	19.1	18.9
Orchard	12.3	11.3	13.2	12.6	11.5	12.7	12.9	12.3	11.9	13.0	12.9	14.2	13.4	13.1	12.7	13.3
Vineyard	2.4	2.6	2.5	2.5	1.6	2.5	2.4	2.4	2.2	2.4	2.4	2.4	2.4	2.4	2.6	2.4
Total	122.6	116.6	124.3	122.2	113.0	119.9	115.7	107.8	108.2	104.5	107.3	103.6	101.6	99.7	95.5	88.7

*Note.* Note that croplands on dairy and organic farms that received land application of manure are excluded from these totals (see text). The ‘VMB’ indicates vegetable, melon, and berries.

under actual irrigation management. Irrigation parameters, including irrigation water amount and efficiency, irrigation frequency, and soil depth of water input, differed among the four irrigation methods and were set based on California conditions (Deng et al., 2018a). Because statewide surveys on irrigation methods of different crop types are only available in 1991, 2001, and 2010, we determined the fractions of irrigation methods for 2001 and 2010 by directly using the survey data and estimated the fractions for nonsurvey years by linearly interpolating or extrapolating the survey data (Table S1 in Supporting Information S1).

Land area of different crop types between 2000 and 2015 was determined based on census and survey data. Specifically, the acreage of each crop in each county was obtained from the Census of Agriculture for 2002, 2007, and 2012, when census data were available (USDA, 2004, 2009, 2014). For the years without census data, we obtained state total area of different crop types from the National Agricultural Statistics Service (NASS, 2016), and allocated the state total acreages per crop to each county based on the area fraction of that crop in that county as interpolated from the census data prior to 2012, or as reported by the California Department of Food and Agriculture after 2012 (CDFA, 2017). Because reliable and complete data regarding application of livestock manure (primarily dairy waste) are lacking, we excluded cropland on dairy and organic farms that received land application of manure from the simulations. The crop types and associated areas in dairy and organic farms were determined based on annual dairy reports and reports of organic agriculture in California (Klonsky and Healy, 2013; Klonsky and Richter, 2007, 2011). After excluding the cropland where manure was applied, the total cropland areas simulated by DNDC ranged between 2.75 and 3.70 million hectares from 2000 to 2015 (Table 1), representing an average of 91.9% (range: 89.4%–93.7%) of total croplands in California.

### 2.3. Direct N<sub>2</sub>O Emissions

The simulations of direct N<sub>2</sub>O emissions were performed by running DNDC with the database containing the spatial and temporal input information. For each year from 2000 to 2015, DNDC was run for three consecutive years for each individual simulation unit possessing unique weather, soil properties, cropping system, and FMPs, using the input information of the unit, with the simulations of the first two years used for model initialization and the N<sub>2</sub>O simulations of the third year used for estimating emissions. We did not run the model for 16 consecutive years from 2000 to 2015 because conducting this simulation requires spatial distributions of each crop type in each year, which were not available.

We simulated the N<sub>2</sub>O emissions under the four irrigation methods separately. For each irrigation method, we conducted around 2100 individual simulations possessing unique weather, soil properties, cropping system, and FMPs. The direct N<sub>2</sub>O emissions under the actual distribution of irrigation management of each year were then calculated by weighting the N<sub>2</sub>O emissions of the individual simulations under the four methods using the fraction of the corresponding irrigation methods for each type of crops (Table S1 in Supporting Information S1). State total N<sub>2</sub>O emissions were calculated by summing the N<sub>2</sub>O emissions from all of the modeling units. In addition, we analyzed the N<sub>2</sub>O emissions from simulated crop types ( $n = 54$ ), crop categories ( $n = 5$ ), and counties ( $n = 58$ ) by summing the N<sub>2</sub>O emissions from the modeling units in each crop type, crop category, or county.

## 3. Results

### 3.1. Cropland Area and N Input

Total simulated cropland area showed a significant decreasing trend ( $P < 0.001$ ; Figure 1a), and reduced by 25% (from  $3,664 \times 10^3$  ha to  $2,747 \times 10^3$  ha) during 2000–2015 (Table 1). Substantial area reductions occurred for hay and field crops and area increased for orchards. From 2000 to 2015, the areas of hay and field crops were reduced by 44% (from  $1,226 \times 10^3$  ha to  $681 \times 10^3$  ha) and 51% (from  $1,031 \times 10^3$  ha to  $507 \times 10^3$  ha), respectively, and the orchard areas were increased by 32% (from  $600 \times 10^3$  ha to  $793 \times 10^3$  ha). N inputs from synthetic fertilizers and crop residues decreased by 23% (from  $653.2 \times 10^6$  kg N to  $505.8 \times 10^6$  kg N), primarily because of cropland area reductions (Figure 1a).

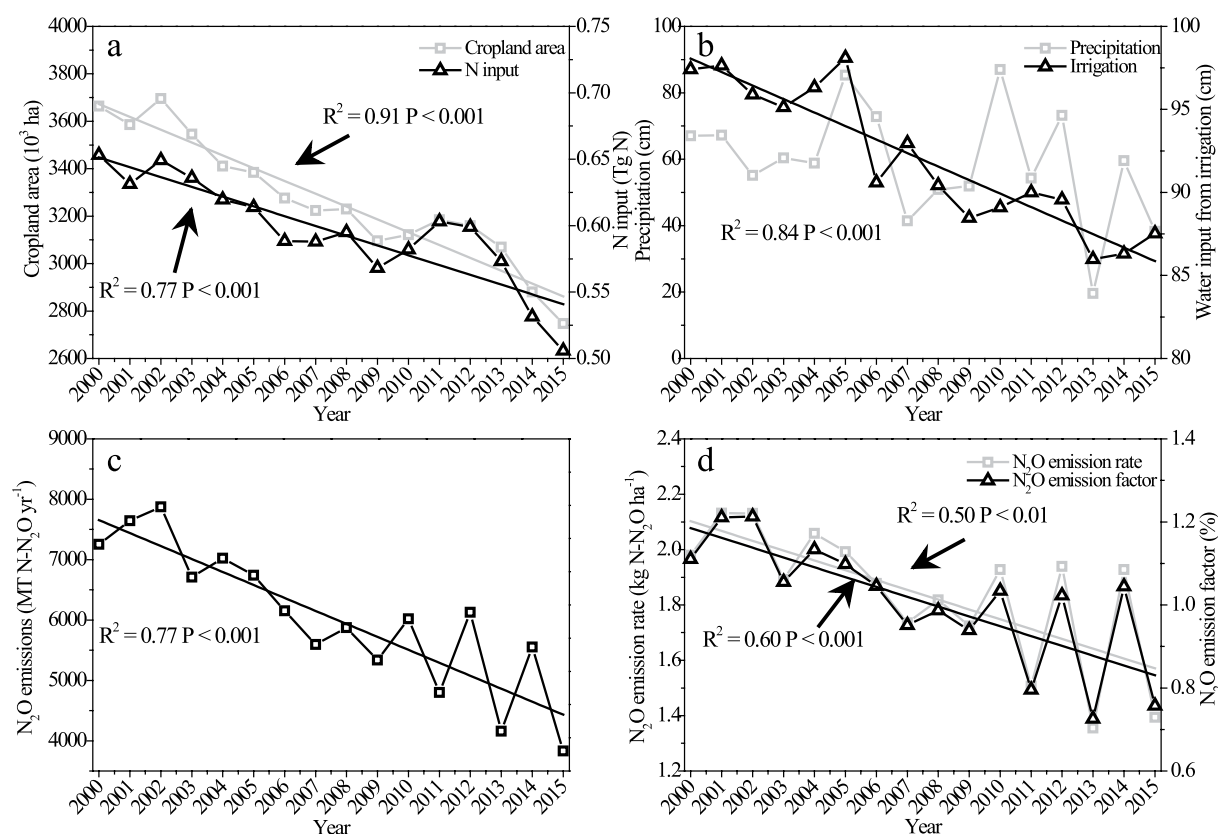
### 3.2. Inventory of N<sub>2</sub>O Emissions

Simulated annual direct N<sub>2</sub>O emissions from California cropland ranged between 3,830 (in 2015) and 7,875 (in 2002) tonnes (t) N<sub>2</sub>O-N yr<sup>-1</sup> during 2000–2015 (Figure 1c); this is 1.79–3.69 Tg CO<sub>2</sub> equivalents yr<sup>-1</sup>, using the 100-year global warming potential of 298 kg CO<sub>2</sub>-equivalents kg<sup>-1</sup> for N<sub>2</sub>O that includes the climate-carbon feedback for both CO<sub>2</sub> and non-CO<sub>2</sub> gases (Stocker et al., 2014). The modeled average annual direct N<sub>2</sub>O emission over this period was 6,044 t N<sub>2</sub>O-N yr<sup>-1</sup> (or 2.83 Tg CO<sub>2</sub> equivalents yr<sup>-1</sup>; Table 2). The uncertainty ranges of annual N<sub>2</sub>O emissions calculated using the “most sensitive factor” method varied from 2,682 to 5,304 t N<sub>2</sub>O-N yr<sup>-1</sup> (2015) and 5,241–11,015 t N<sub>2</sub>O-N yr<sup>-1</sup> (2002). On average, the range of likely N<sub>2</sub>O emissions due to varying soil properties was 68%–139% of the “representative” N<sub>2</sub>O emissions from 2000 to 2015, which were simulated using area-weighted average soil property values. The DNDC-based N<sub>2</sub>O emission factor (EF; defined as fraction of the N input from synthetic fertilizers and crop residues directly emitted as N<sub>2</sub>O) ranged from 0.73% (in 2013) to 1.21% (in 2001 and 2002) during 2000–2015. The simulated average fraction of the N input emitted as N<sub>2</sub>O was 1.01% over this period.

Most of the N<sub>2</sub>O emissions were from hay and field crops during the simulated years, although the contributions of different crop categories were variable across the years (Figure 2). On average, 37% and 36% of the state total N<sub>2</sub>O emissions were from the hay (including pasture, non-legume hay, and alfalfa) and field crops during 2000–2015, respectively. The average contributions of VMB, orchards, and vineyards to the state simulated total N<sub>2</sub>O emissions were 13%, 9%, and 4%, respectively (Figure 2). The simulated annual N<sub>2</sub>O emission rates from 2000 to 2015 were highest for field crops (mean: 2.67 kg N<sub>2</sub>O-N ha<sup>-1</sup>), followed by hay (mean: 2.20 kg N<sub>2</sub>O-N ha<sup>-1</sup>), VMB (mean: 1.78 kg N<sub>2</sub>O-N ha<sup>-1</sup>), and vineyards (mean: 0.80 kg N<sub>2</sub>O-N ha<sup>-1</sup>; Figure 3).

We summarized N<sub>2</sub>O emissions from different crop types based on average results of the multiyear's simulations (Table 2). The individual crops with large contributions to the state total N<sub>2</sub>O emissions were corn (15.9%, including grain corn and silage corn, but excluding corn systems with manure amendment), non-legume hay





**Figure 1.** Total cropland area and nitrogen (N) input from synthetic fertilizers and crop residues (a), annual total precipitation and irrigation water input (b), annual total simulated nitrous oxide (N<sub>2</sub>O) emission (c), and state average emission rates and N<sub>2</sub>O Emission Factors (EFs) (d) from 2000 to 2015 for California. EFs in panel (d) are the fractions of N input from synthetic fertilizers and crop residues directly emitted as N<sub>2</sub>O. The statistical results are for the corresponding regression lines. Significant decreasing trends were identified for cropland area, N input, water input from irrigation, state total N<sub>2</sub>O emissions, and state average N<sub>2</sub>O emission rate and EF for the croplands simulated by DeNitrification-DeComposition. There was no significant decreasing trend for annual total precipitation.

(15.8%), pasture (13.4%), alfalfa (8.1%), and cotton (6.1%). These crop types had high simulated N<sub>2</sub>O emissions primarily because of their large cultivation areas, high N inputs of synthetic fertilizers or crop residues (Table 2), and/or high water inputs due to a large percentage of low-efficiency surface gravity irrigation (Table S1 in Supporting Information S1).

Total simulated mean annual N<sub>2</sub>O emissions from 2000 to 2015 varied by county within a range of 0.0 to >480 t N<sub>2</sub>O-N yr<sup>-1</sup> (Figure 4). The counties with substantial simulated N<sub>2</sub>O emissions were mostly located in the Central Valley (Figures 4; S4 in Supporting Information S1). San Joaquin County had the highest N<sub>2</sub>O emissions, on average accounting for 9.0% of state total N<sub>2</sub>O emissions from 2000 to 2015. Fresno and Tulare Counties contributed 7.2% and 6.9%, respectively, followed by Monterey (6.0%) and Merced (5.7%) Counties (Figure 4). The spatial variations in total N<sub>2</sub>O emissions were due to the differences in not only cropland area and associated fertilizer N application but also other environmental factors, such as climate, crop types, and soil properties, which resulted in a variation range of 0.15–14.1 kg N ha<sup>-1</sup> year<sup>-1</sup> for the simulated mean annual N<sub>2</sub>O emission rates from 2000 to 2015 across different counties.

### 3.3. Temporal Trend of N<sub>2</sub>O Emissions

Simulated direct N<sub>2</sub>O emissions from California cropland showed a significant decreasing trend from 2000 to 2015 ( $P < 0.001$ ; Figure 1c), with state cropland N<sub>2</sub>O emissions declining by 47% (from 7,254 t N<sub>2</sub>O-N to 3,830 t N<sub>2</sub>O-N) over this period. The decline was due to significant reductions of not only cropland area and N inputs (Figure 1a) but also the state average N<sub>2</sub>O emission rate ( $P < 0.001$ ; Figure 1d) and EF ( $P < 0.01$ ; Figure 1d). The decreasing trends of the state average N<sub>2</sub>O emission rate and EF were likely due to the trend of growing more orchard crops and less hay and field crops (Table 1), combined with lower N<sub>2</sub>O emission rates for orchards

**Table 2**

*Average Total Cropland Area Used for Simulating the Direct N<sub>2</sub>O Emissions, N Inputs From Synthetic Fertilizers and Crop Residue, and N<sub>2</sub>O Emission From 2000 to 2015, and Changes of the Cropland Area, N Inputs, and Direct N<sub>2</sub>O Emission From 2000 to 2015*

Crop type	Means from 2000 to 2015			Changes from 2000 to 2015		
	Area	N input	N <sub>2</sub> O	Area	N input	N <sub>2</sub> O
	ha	t N	t N <sub>2</sub> O-N	ha	ha	t N <sub>2</sub> O-N
Alfalfa	403,521	57,024	491.2	−115,000	−16,853	−228.0
Almonds	267,778	62,407	204.7	151,502	35,255	68.3
Apples	8,607	513	2.5	−10,625	−621	−2.8
Apricots	4,606	432	2.0	−3,200	−300	−2.0
Artichokes	2,973	752	6.9	−1,070	−270	−3.6
Asparagus	8,127	822	5.2	−10,602	−1073	−9.7
Avocados	22,275	4,284	18.8	−3,784	−725	−6.4
Barley	25,165	3,332	37.7	−29,488	−3,883	−46.2
Beets	14,955	3,641	21.6	−6,671	−1641	−29.6
Berries	15,151	3,571	41.1	6,606	1572	13.7
Broccoli	46,305	11,159	126.3	−7,619	−1815	−61.0
Cabbage	6,645	2,216	29.5	−2,490	−829	−21.3
Carrots	21,404	6,569	25.5	−4,278	−1,291	−8.0
Cauliflower	13,272	3,733	27.5	−2131	−598	−10.4
Celery	5,941	2,935	32.8	−5,809	−2,897	−36.8
Cherries	10,708	853	3.4	4,289	331	−0.5
Cotton	192,833	43,153	366.5	−306,327	−68,473	−705.3
Dates	2,028	958	0.8	1931	966	0.4
Dry beans	26,071	3,339	80.1	−27,454	−3,609	−72.8
Figs	3,549	411	1.0	−2,694	−312	−1.2
Garlic	9,712	3,182	12.0	−2,451	−783	−12.2
Grain corn	67,925	25,013	537.1	−59,490	−21,902	−569.1
Grapes	311,438	16,395	248.8	2,137	89	−75.4
Green beans	8,314	1,471	17.6	−6,682	−1,209	−16.9
Lemons	18,821	4,601	12.4	−1329	−502	−4.3
Lettuce	84,408	18,991	149.7	−11,109	−2,557	−107.3
Melons	25,696	5,812	46.1	−9,452	−2,156	−19.1
Non-legume hay	286,642	47,342	954.0	−50,491	−8,296	−318.5
Oats	2,002	216	0.8	−2374	−247	−0.5
Olives	13,646	1,660	12.3	−774	−84	−0.4
Onions	17,152	4,705	21.4	2,019	509	−18.7
Other citrus	89,825	14,309	39.8	−1,463	−1030	−12.0
Other fruits	7,218	1,384	4.8	12,279	2351	8.0
Other nuts	90,266	21,657	155.5	39,015	9,395	52.7
Other vegetables	17,654	3,967	24.9	20,403	4,620	18.9
Pasture	324,946	34,161	812.7	−379040	−39789	−899.1
Peach	35,428	6,785	26.2	−27,603	−5,283	−22.4
Pears	5,958	1,266	3.5	−3,731	−826	−2.8
Peppers	10,385	3,369	11.5	−69	−16	−7.4

**Table 2**  
*Continued*

Crop type	Means from 2000 to 2015			Changes from 2000 to 2015		
	Area	N input	N <sub>2</sub> O	Area	N input	N <sub>2</sub> O
	ha	t N	t N <sub>2</sub> O-N	ha	ha	t N <sub>2</sub> O-N
Pistachios	54,148	11,397	33.2	63,845	13,438	38.0
Plums	12,231	1864	7.2	−8,679	−1318	−4.3
Potatoes	15,059	3,797	11.5	−3,911	−984	−4.4
Prunes	25,717	5,052	20.8	−16,099	−3,124	−15.7
Rice	211,729	33,107	320.3	−51,191	−8,491	−42.6
Safflowers	27,127	3,457	13.9	−14,831	−1,877	−5.5
Silage corn	86,903	25,669	425.1	19,895	5,908	109.4
Sorghum	8,760	1,863	10.3	20,462	4,297	19.7
Spinach	9,201	1,502	14.4	−2,507	−402	−16.0
Spring wheat	48,189	16,688	143.2	−113	−81	7.8
Squash	4,796	1,703	18.6	−1195	−425	−5.1
Sunflowers	13,083	1,394	14.2	6,585	698	4.4
Sweet potatoes	5,008	786	3.7	2,407	383	0.5
Tomatoes	128,340	35,167	191.2	−3,517	−1,589	−142.8
Winter wheat	88,041	24,329	199.7	−72,886	−20,236	−198.9
Hay	1,015,109	138,527	2,258	−544,531	−64,938	−1,446
Field crops	812,781	185,205	2,171	−523,882	−119,535	−1,529
VMB	455,543	116,209	817	−43,457	−11,810	−468
Orchard	672,809	139,833	549	192,880	47,611	93
Vineyard	311,438	16,395	249	2137	89	−75
Total	3,267,680	596,169	6,044	−916,853	−148,583	−3,425

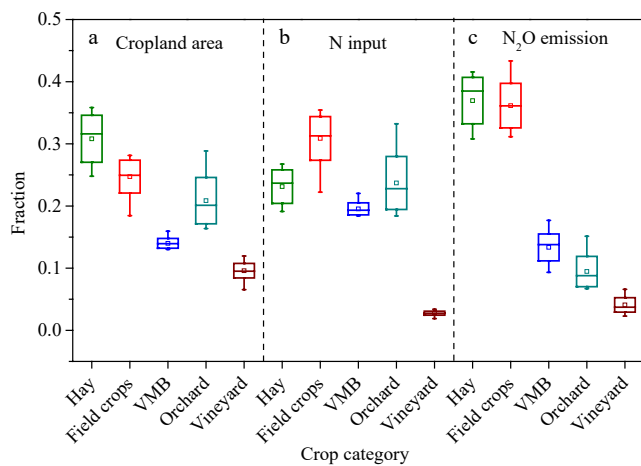
*Note.* We aggregated results of the 54 crops into five crop categories—hay, field crops, vegetable-melon-berries (VMB), orchard, and vineyard. Hay includes alfalfa, non-legume hay, and pasture. VMB includes artichokes, asparagus, berries, broccoli, cabbage, carrots, cauliflower, celery, garlic, green beans, lettuce, melons, onions, other vegetables, peppers, potatoes, spinach, squash, sweet potatoes, and tomatoes. Orchard include almonds, apples, apricots, avocados, cherries, dates, figs, lemons, olives, other citrus, other fruits, other nuts, peach, pears, pistachios, plums, and prunes. Vineyard is grapes. All other crops were aggregated into field crops.

(Figure 3b). The decrease in the state simulated average N<sub>2</sub>O emission rate also resulted from the decrease of surface gravity and increase in the low-volume drip irrigation from 2000 to 2015 (Figure S3 in Supporting Information S1). This trend resulted in a reduction of irrigation water input per hectare (Figure 1b), and a reduction of the N<sub>2</sub>O emission rate because of lower emission rates under low-volume irrigation (Deng et al., 2018a).

Decreasing N<sub>2</sub>O emission trends were significant for hay, field crops, and VMB crop categories ( $P < 0.001$  for the hay and field crops and  $P < 0.01$  for the VMB, Figure 3a). DNDC simulated substantial reductions of 1446 t N<sub>2</sub>O-N (reduced by 53%) for hay and of 1529 t N<sub>2</sub>O-N (reduced by 55%) for field crops from 2000 to 2015, which accounted for 42% and 45% of the state total reduction (3,425 t N<sub>2</sub>O-N), respectively. The decreasing trends of the N<sub>2</sub>O emissions from these two categories were largely due to the reductions of their croplands area and N inputs (Table 1). The simulated N<sub>2</sub>O emissions between 2015 and 2000 from VMB were reduced by 47% (468 t N<sub>2</sub>O-N) although the areas of VMB were decreased by only 9%. No significant trend was identified for the N<sub>2</sub>O emissions from orchards or vineyard although the orchard areas were increased by 32% from 2000 to 2015.

Decreasing trends in the N<sub>2</sub>O emissions were estimated for most counties in California (Figure 5), although several counties showed slight increases between 2000 and 2015. The reductions in simulated N<sub>2</sub>O emissions varied by county within a range of 0.0 to >300 t N<sub>2</sub>O-N yr<sup>−1</sup> (Figure 5).





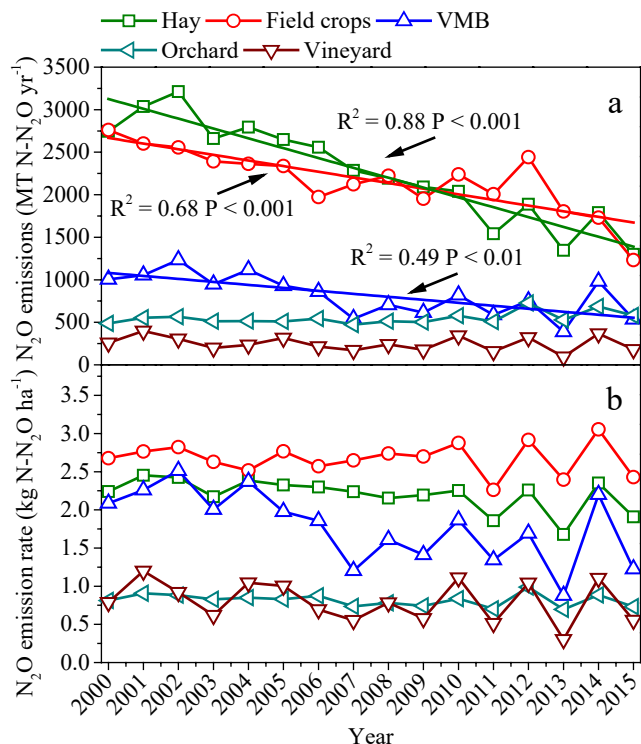
**Figure 2.** Fractions of hay, field crops, vegetable-melon-berries, orchard, and vineyard in all simulated crops for (a) cropland area, (b) Nitrogen input from synthetic fertilizers and crop residues, and (c) direct nitrous oxide emissions. Bars indicate minimum and maximum fractions, boxes represent the standard deviation and median fraction, and squares represent the average fractions from 2000 to 2015. In any year, all fractions add to 1.0.

## 4. Discussion

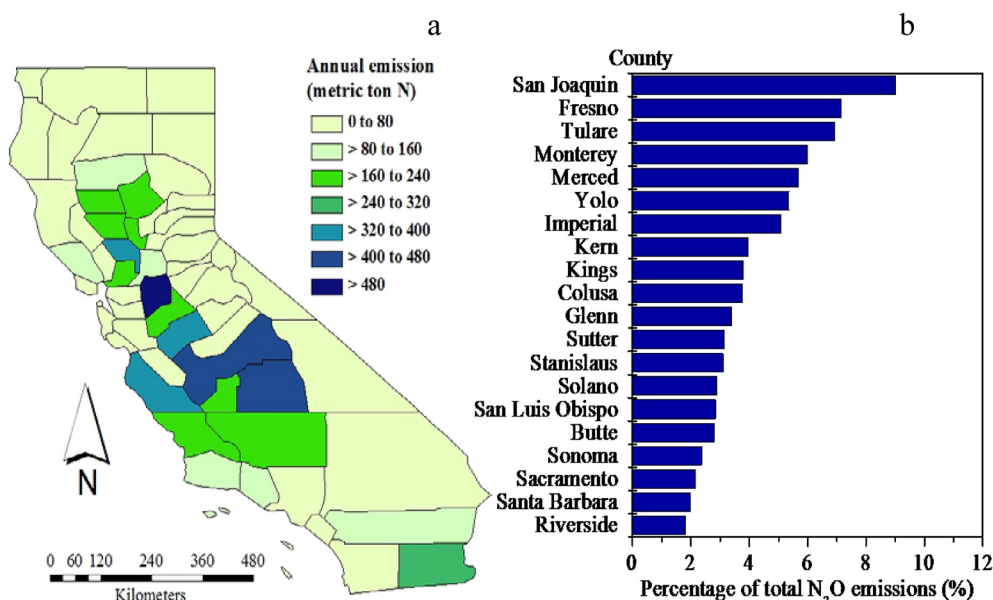
We estimated multiyear  $\text{N}_2\text{O}$  emissions from California cropland using the process-based DNDC model. According to IPCC GHG inventory guidelines (Eggleston et al., 2006), process-based simulation, a Tier 3 approach, is the recommended methodology to calculate a regional  $\text{N}_2\text{O}$  inventory from cropland. We compared the DNDC-based estimations with the  $\text{N}_2\text{O}$  emissions developed by California Air Resource Board (CARB) using the IPCC EF methodology (i.e., the Tier 1 approach that used solely a fixed EF; CARB, 2016), including direct  $\text{N}_2\text{O}$  emissions from N inputs through applications of synthetic fertilizers and crop residues. The average direct  $\text{N}_2\text{O}$  emission using the IPCC EF methodology was  $2.67 \text{ Tg CO}_2 \text{ equivalents yr}^{-1}$  during 2000–2014 (CARB, 2016), which is comparable with the average calculated from simulated  $\text{N}_2\text{O}$  emissions ( $2.90 \text{ Tg CO}_2 \text{ equivalent yr}^{-1}$  from 2000 to 2014).

However, the interannual variability and temporal trend of the state total  $\text{N}_2\text{O}$  emissions were different between the DNDC and EF methods. The state total  $\text{N}_2\text{O}$  emissions estimated using DNDC (range:  $1.79$  to  $3.69 \text{ Tg CO}_2 \text{ equivalents yr}^{-1}$ ; Figure 1) showed a higher interannual variability than  $\text{N}_2\text{O}$  emissions based on the EF method (range:  $2.43$  to  $2.82 \text{ Tg CO}_2 \text{ equivalents yr}^{-1}$ ; CARB, 2016). DNDC predicted higher interannual variability because the simulations considered interannual changes in both environmental factors and human activities that could regulate  $\text{N}_2\text{O}$  emission while the EF method only considered the temporal change of N input and used a fixed EF (CARB, 2016). For example, we identified that the relatively large interannual variability of the DNDC-based  $\text{N}_2\text{O}$  emissions and state average EFs (range:  $0.73\%$ – $1.21\%$ ) may have been due to the large interannual changes of water inputs. The simulated  $\text{N}_2\text{O}$  emissions from 2000 to 2015 were significantly correlated with the precipitation ( $P < 0.05$ ) and irrigation water inputs per hectare ( $P < 0.001$ ). The DNDC-based EFs are comparable with the EFs ( $0.68\%$  for low-volume irrigation systems and  $0.98\%$  for high-volume irrigation systems) developed by summarizing  $\text{N}_2\text{O}$  measurements in Mediterranean climate cropping systems (Aguilera et al., 2013). However, neither precipitation nor irrigation are considered by the EF method.

Furthermore, DNDC predicted a significant decreasing trend for state total direct  $\text{N}_2\text{O}$  emissions from 2000 to 2015 (Figure 1c). The decreasing trend can be explained by the reductions in the cropland area. For example, Johnson and Cody (2015) and Cooley et al. (2015) estimated that total area of field crops, fruits and nuts, vegetables and melons reduced by  $13.5\%$  during 2000–2009 and  $12.7\%$  during 2000–2014, respectively, in California. These values were comparable with our estimated corresponding reductions of  $13.1\%$  and  $15.4\%$  for these three categories. The decreasing trend may be associated with regional urbanization of croplands (in particular for hay and field crops; Wilson et al., 2016), and with the drought in California from 2012 to 2016 (Cooley et al., 2015; Gebremichael et al., 2021; Griffin and Anchukaitis, 2014). The trend of growing more high value orchard crops with low-volume and high-frequency irrigation systems and increasing crop water use efficiency (Johnson and Cody, 2015; Sleeter et al., 2017) may lead to further declines of the direct  $\text{N}_2\text{O}$  emissions. However, we note that cropland reductions due to drought were temporary, and will therefore not continue to reduce  $\text{N}_2\text{O}$  emissions. Given that the cropland area may further decrease driven by California's continued population growth and housing development projections (Mann et al., 2014; Sleeter et al., 2017; Wilson

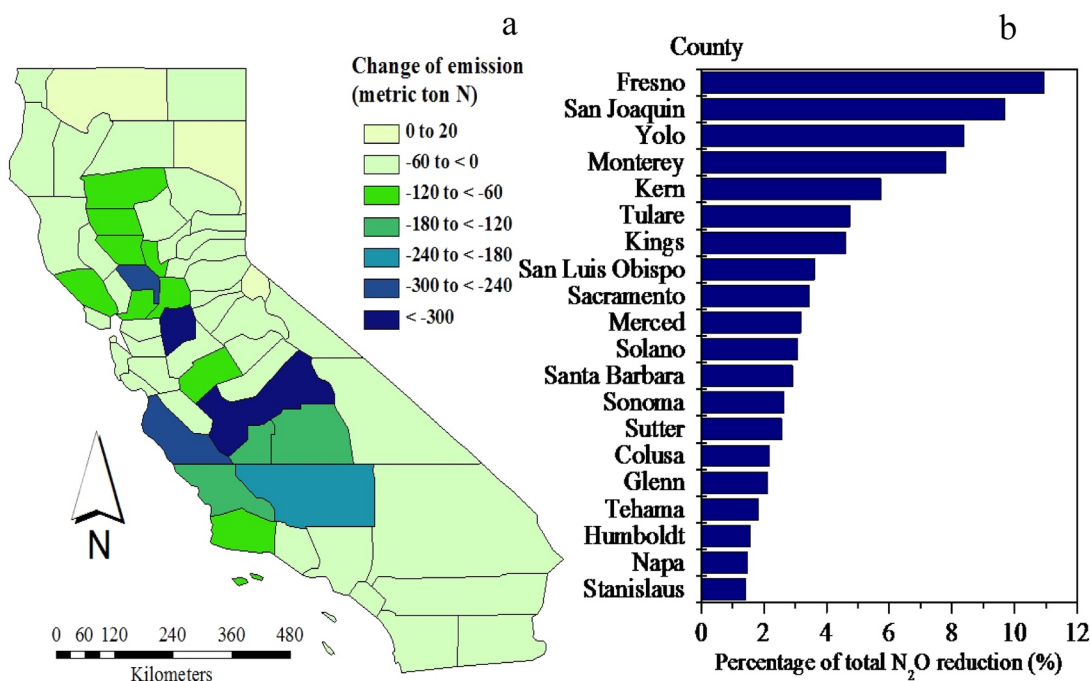


**Figure 3.** Aggregate annual total nitrous oxide ( $\text{N}_2\text{O}$ ) emissions (a) and average  $\text{N}_2\text{O}$  emission rate (b) for hay, field crops, vegetable-melon-berries (VMB), orchard, and vineyard from 2000 to 2015. The statistical results are for the corresponding regression lines. Significant decreasing trends were identified for annual total  $\text{N}_2\text{O}$  emissions for the hay, field crops, and VMB.



**Figure 4.** DeNitrification-DeComposition simulated aggregate annual nitrous oxide (N<sub>2</sub>O) emissions from counties in California (a), and a ranking of the top 20 counties based on N<sub>2</sub>O emissions (b). The data in panel (a) are mean annual N<sub>2</sub>O emissions from 2000 to 2015. The sum of the N<sub>2</sub>O emissions from these 20 counties was over 80% of the state total N<sub>2</sub>O emission.

et al., 2016), direct N<sub>2</sub>O emissions from California cropland may decrease. However, based on a study by Haden et al. (2013), GHG emissions per hectare of urbanized land are substantially larger than those per hectare of cropland in California. Therefore, the identified reductions in direct N<sub>2</sub>O emissions from cropland due to urbanization do not imply a reduction in total regional GHG emissions, and urbanization should not be viewed as a mitigation approach for GHG emissions.



**Figure 5.** Change in annual nitrous oxide (N<sub>2</sub>O) emissions (2015 minus 2000) for counties in California (a), and a ranking of the top 20 counties based on reduction of N<sub>2</sub>O emissions (b). Most counties had a reduction in N<sub>2</sub>O emissions. The sum of the N<sub>2</sub>O reduction from these 20 counties was over 80% of the state total N<sub>2</sub>O reduction.

In addition to the reductions in the total cropland areas and N inputs identified in this study (Figure 1a) and reported by other studies (Johnson and Cody, 2015; Rosenstock et al., 2013; Wilson et al., 2016), the DNDC-based estimations include impacts of other changes on reducing N<sub>2</sub>O emissions. First, DNDC predicted crop-specific N<sub>2</sub>O emission rates by considering detailed FMPs for each crop type. The simulated N<sub>2</sub>O emission rates for orchards were generally lower than that of hay or field crops (Figure 3b). Therefore, the trend toward growing more orchards crops and less hay and field crops during 2000–2015 (Table 1; Johnson and Cody, 2015) contributed to the decline in the state total N<sub>2</sub>O emissions. The inter annual changes of precipitation correlated with simulated state total N<sub>2</sub>O emission ( $R^2 = 0.35$ ,  $P < 0.05$ ), although precipitation did not show a significant decreasing trend from 2000 to 2015. In addition, our earlier work suggested that changes in irrigation management in California croplands (Figure S3 in Supporting Information S1) have likely reduced N<sub>2</sub>O emissions (Deng et al., 2018a). The results of relatively low N<sub>2</sub>O emission rates for orchards or under low-volume and high-frequency irrigation suggest that changing crop type and improving irrigation practices have the potential to reduce N<sub>2</sub>O emissions from California cropland.

We also quantified variations in N<sub>2</sub>O emissions among different cropping systems and counties. Substantial N<sub>2</sub>O emissions were simulated for the Central Valley (Figures 4; S4 in Supporting Information S1), consistent with estimates of California's total anthropogenic N<sub>2</sub>O emissions based on a top-down inverse method (Jeong et al., 2018). Total cropland N<sub>2</sub>O emissions varied substantially across different counties (Figures 4; S4 in Supporting Information S1), driven by differences in not only cropland area and fertilization but also climate, soil, and FMPs other than fertilization (e.g., crop type, irrigation). The simulated average annual N<sub>2</sub>O emission rates per hectare from 2000 to 2015 across different counties were positively correlated with the precipitation ( $R^2 = 0.39$ ,  $P < 0.001$ ) and SOC ( $R^2 = 0.72$ ,  $P < 0.001$ ) and negatively correlated with the soil pH ( $R^2 = 0.28$ ,  $P < 0.001$ ). The simulated impacts on N<sub>2</sub>O emissions of these environmental factors are consistent with studies that investigated controlling factors of N<sub>2</sub>O emissions from croplands (e.g., Bouwman et al., 2002; Shcherbak et al., 2014). Most of these factors are not considered by the EF methodology, although they are necessary for more fully characterizing the variability of N<sub>2</sub>O emissions across different cropping systems or regions, and can provide insight for developing mitigation strategies for N<sub>2</sub>O emissions (Eagle and Olander, 2012; Smith et al., 2008). By considering the influences of both environmental factors and a more complete range of human management activities, process-based models, such as DNDC, can provide an improved characterization of the spatial-temporal dynamics of direct N<sub>2</sub>O emissions from regions with diverse agriculture compared to the EF approach.

Given as a statewide multiyear analysis, we recognize that the simulations are subject to uncertainties and limitations in model representation and activities database. Large uncertainties were estimated for simulated direct N<sub>2</sub>O emissions due to variability of soil properties (a range of 68%–139% of the “representative” N<sub>2</sub>O emissions). We note that these uncertainties should not be interpreted as random errors confounding the significant decreasing trend of the N<sub>2</sub>O emissions from 2000 to 2015, because the temporal change of the N<sub>2</sub>O emissions resulted from interannual variations in areas of different crop types and FMPs, instead of the interannual or spatial variation of the soil properties. Another limitation of our simulations is that we excluded N inputs from manure amendments, due to insufficient activity data on manure application (i.e., manure rate and type, timing and location of application, and method of application). Both the EF approach and top-down inverse method suggested that livestock manure applied to cropland may represent an important source of N<sub>2</sub>O emissions in California (CARB, 2016; Guha et al., 2015), although cropland on dairy and organic farms represents only about 8% of state total cropland. Therefore, N<sub>2</sub>O emissions from livestock manure should be further characterized through incorporating N inputs from manure application into the regional database and linking the model and the database. In addition, the simulations of N<sub>2</sub>O emissions from California pasture land have not been tested against field measurements as there are no field data of N<sub>2</sub>O emissions from pasture in California. Therefore, further model testing on N<sub>2</sub>O emissions from California pasture land should be performed to constrain the simulated N<sub>2</sub>O emissions from pasture.

## 5. Conclusions

We applied a process-based biogeochemical model, DNDC, to quantify temporal and spatial dynamics of direct N<sub>2</sub>O emissions from California cropland with highly diverse cropping systems and FMPs. The simulated direct N<sub>2</sub>O emissions ranged from 3,830 to 7,875 t N<sub>2</sub>O-N yr<sup>−1</sup> (or 1.79 to 3.69 Tg CO<sub>2</sub> equivalents yr<sup>−1</sup>) during 2000–

2015, representing 0.73%–1.21% of the N inputs from synthetic fertilizers and crop residues. Simulated direct N<sub>2</sub>O emissions decreased by 47% (from 7,254 t N<sub>2</sub>O-N to 3,830 t N<sub>2</sub>O-N) between 2000 and 2015, most likely due to reductions of total cropland area and associated N inputs, the trend toward growing more orchard crops and less hay and field crops, and changes in irrigation management practices although N<sub>2</sub>O emissions varied also due to climate, soil properties, and FMPs other than N fertilization. Simulated N<sub>2</sub>O emissions were highly variable across different cropping systems and counties. The counties with the greatest simulated N<sub>2</sub>O emissions were mostly located in the Central Valley and important contributing crops were corn, non-legume hay, pasture, alfalfa, and cotton. Overall, the temporal dynamics of the simulated direct N<sub>2</sub>O emissions and the factors affecting the long-term trend identified in our study indicate that process-based models, such as DNDC, provide more detailed knowledge than the IPCC Tier 1 EF approach and can be useful for designing strategies toward effective N<sub>2</sub>O mitigation in regions with diverse croplands.

## Data Availability Statement

The DNDC model, database for driving the model, and all data used in this study are archived at the figshare repository (<https://doi.org/10.6084/m9.figshare.16909405>).

## Acknowledgments

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