



Compost Soil Amendment Impacts on Greenhouse Gases

Produced Under Contract By: Whendee L. Silver, Yocelyn Villa, Mu Hong, Lidong Li,
Yao Zhang, and Keith Paustian



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Public Affairs Office
1001 I Street (MS 22-B)
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Produced Under Contract By:

Whendee L. Silver

Department of Environmental Science, Policy, and Management, University of
California, Berkeley

Yocelyn Villa

Silver Lab, Department of Environmental Science, Policy, and Management,
University of California, Berkeley

Keith Paustian

Department of Soil and Crop Science and Natural Resource Ecology Laboratory,
Colorado State University

Mu Hong

Natural Resource Ecology Laboratory, Colorado State University

Lidong Li

Department of Soil and Crop Science, Colorado State University

Yao Zhang

Natural Resource Ecology Laboratory, Colorado State University

Under CalRecycle Direction By:

Kristen Pidcock

Senior Environmental Scientist

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Executive Summary

Senate Bill 1383 (Lara, Chapter 395, Statutes of 2016) is part of California's landmark efforts to address climate change by reducing and recycling waste through improved capture and composting of organic materials. Compost application to agricultural lands is a practice that is increasing in California and nationally given growing interest in sustainable or regenerative agriculture, improvements in organic waste management, and adoption of circular economy principles. Compost application is also one of the management practices that the California Air Resource Board and the State of California are including in their climate change assessment modeling and planning processes.

Rangelands cover approximately 40% of California's land area and have been shown to contribute to climate change mitigation when amended with compost. To better understand the potential benefits of compost amendments to rangelands throughout the state, biogeochemical models are needed to scale up results from field-based studies. Current process-based ecosystem biogeochemical models do not explicitly include the algorithms needed to accurately predict the impacts of compost amendments on rangeland. Additions and adjustments to model components are needed to better represent the diversity of compost types in terms of decomposition and stabilization rates in soil, as well as nitrogen immobilization and mineralization rates and nitrous oxide (N_2O) emissions from soils that have received compost. A major limiting factor to date has been a scarcity of field studies of N_2O emissions following compost amendments.

The goal of this project was to evaluate the functionality of the DayCent biogeochemical model for compost applications with special reference to N_2O emissions and develop approaches to improve model performance. The specific objectives were to:

1. Use data from a laboratory experiment to identify specific relationships between composts of different chemical quality and greenhouse gas emissions using a control soil.
2. Use data from a laboratory experiment to determine the specific relationships between a control compost and greenhouse gas emissions across soils of different chemical or physical characteristics.
3. Identify patterns in greenhouse gas emissions following compost amendments to soils using data gathered from the literature.
4. Use the information generated to adjust model parameters to better represent field results for greenhouse gas emissions from compost amendments.

Key Findings

1. N_2O fluxes following compost amendments of different initial feedstocks and chemical quality were generally low. Vermicompost exhibited higher nitrate (NO_3^-) concentrations, hot moments of N_2O emissions, and more variable N_2O emissions.

2. Larger N₂O fluxes occurred shortly after a wet-up event in compost-amended soils, in the control and were particularly high in the vermicompost treatment. This highlights the pulse dynamics of this greenhouse gas. Significantly higher N₂O emissions following the wet-up event demonstrate the importance of capturing event-based fluxes.
3. Soils amended with vermicompost exhibited higher methane (CH₄) emissions, likely driven by soil inoculation of methanogens from earthworm guts.
4. Compost application to soils collected during the wet season resulted in higher N₂O emissions relative to unamended soils. The emissions were generally low and decreased after the first one to two weeks.
5. The literature study provided an assessment of the range of compost properties, soil conditions, climate, and N₂O fluxes for agricultural sites. Relatively few data were available for rangelands. These data were used for model parameterization (environmental and compost variables) and validation (N₂O fluxes).
6. A Bayesian calibration approach, simultaneously targeting multiple biogeochemical variables (soil carbon (C) and nitrogen (N), N₂O and carbon dioxide (CO₂) emissions, and biomass C and N), improved model performance for the prediction of those variables in the DayCent model.
7. Including key parameters in the Bayesian calibration, such as a parameter [CULTRA(6)] to account for the initial distribution among pools, improved DayCent model performance on carbon and nitrogen simulations for compost sites.
8. The high spatial and temporal variability typical of N₂O emissions makes them difficult to model with high accuracy. The laboratory, literature, and modeling research conducted as part of this contract improved model performance and identified future areas of potential improvement, particularly the need for more high-resolution N₂O flux data.

Recommendations

The findings from this research provide the most comprehensive assessment to date of mechanistic drivers and field flux data for compost amendments to rangeland soils. While we were able to improve performance of the DayCent model, future work using continuous flux data is likely to provide the high resolution needed for the next generation of model improvements. The research yielded the following specific recommendations:

1. The high temporal variability of N₂O requires continuous flux data to make the next generation improvements to biogeochemical modeling of N₂O. These types of data with detailed documentation should be incorporated into model development as they become available and are likely to greatly improve model performance.
2. Process-based models should develop specific parameters to account for the distribution of compost C and minerals within and between surface and soil pools to improve the compost representation in the model.

3. Vermicompost has the potential to increase CH₄ emissions, and possibly N₂O emissions after wet-up, from soils following application. The impacts of vermicompost should be followed in field studies, and management adapted accordingly (e.g., avoid saturated soil conditions).

Report

Introduction

Compost application is one of the management practices that the California Air Resources Board and other state agencies are using in their climate change assessment modeling and planning processes. Compost application to rangeland is a practice that is likely to substantially increase in California and nationally given the growing interest in sustainable/regenerative agriculture, improvements in organic waste management, and adoption of circular economy principles. Additionally, compost application is now included as a conservation practice standard by the Natural Resources Conservation Service, allowing producers using this conservation practice to receive funds from the U.S. Department of Agriculture Environmental Quality Incentive Program (EQIP USDA CPS 336). Compost amendments to soils have been shown to increase soil organic matter content, improve water holding capacity, stimulate plant growth, and help lower atmospheric carbon dioxide (CO₂) (Ryals and Silver 2013, Flint et al. 2018, Kutos et al. 2023, Mayer et al. 2022). Research from field experiments and laboratory studies in California suggested that compost amendments to soils result in little or no increase in nitrous oxide (N₂O) emissions, a potent greenhouse gas (Ryals and Silver 2013, Anthony et al. 2024, 2025). However, a widely used computer model, DayCent, overestimated N₂O emissions from compost-amended soils in grasslands when compared with field and laboratory data in California and Europe (Ryals et al. 2015, Martins et al. 2022). The DayCent model is widely used to determine the potential impacts of scaling up climate change mitigation practices, as well as facilitating carbon (C) accounting at regional, state, and national levels. The goal of this project was to improve the functionality of the standard version of the DayCent model for simulating compost applications to California rangelands by exploring basic mechanistic biogeochemical relationships driving C and nitrogen (N) dynamics including N₂O emissions following compost application via laboratory experiments and published literature. We then critically evaluated the model performance for N₂O emissions based on these mechanistic criteria and modified the model parameters accordingly to better represent emissions following compost applications to soils.

The research conducted for this project included laboratory studies, a literature review and assessment, and model testing. In the laboratory, experiments were conducted to assess the N₂O emissions from the application of composts with different chemical characteristics, and compost application to soils with different physical and biogeochemical properties. The experiments were used to provide targeted data on key drivers of N₂O emissions to better represent these processes in the DayCent biogeochemical model. The literature review and assessment aimed to summarize the existing knowledge base and provide additional data for parameterization, calibration,

and validation of the modeling work. Finally, the modeling research consisted of comparative analyses of model, field, and lab data, and associated adjustments to the model parameters to better represent the general patterns in the empirical data.

Approach

Laboratory Experiments

The first experiment tested the biogeochemical effects of composts of different chemical qualities (defined by the ratio of C to N, termed C:N). The DayCent model uses the compost C:N ratio as an important driver of N₂O fluxes. Soils were collected from the Nicasio Native Grass Ranch in Marin County in September 2023; the site was the same as the control plot referred to as Wick Ranch Block 5 from Ryals et al. (2014) and is referred to here as WR 5. Soils are classified in the Tocaloma-Saurin-Bonnydoon series as Haploserolls and Argixerolls great groups and are derived from Franciscan mélange (Beaudette and O'Geen, 2009). The percentages of clay, silt, and sand are 16%, 41%, and 43%, respectively, for the field site used in this experiment. Replicate samples (0-10 cm depth) were amended with one of three composts (Table 1):

- Nicasio Blend from West Marin Compost of Marin, CA, derived from recycled yard trimmings, dairy manure and horse manure with a C:N ratio of 22.
- Hi-Test from West Marin Compost of Marin, CA, made from recycled yard trimmings, dairy, horse, chicken, and goat manure with high N and a C:N ratio of 17.
- Vermicompost from Jepson Prairie Organics of Vacaville, CA, composed of recovered yard trimmings and food scraps fed to Red Wiggler worms. The final compost product contained worm castings and had a C:N ratio of 13.

We chose the composts to represent a range of values for the C:N ratio as these are one of the primary predictors of biogeochemical dynamics and N cycling in the model. While the DayCent model does not specifically consider compost feedstock composition or production management, it does utilize information on the basic chemical characteristics including N concentrations and C:N ratio.

Application rates were equivalent to 65.5 g total N/m² for all composts and thus we added 8.5 g for Nicasio Blend; 14.8 g for the vermicompost; and 15.6 g for the Hi-Test compost to 200 g of soil at field-moisture. The amount of C added to the soils was 1441 g C/m², 1113.5 g C/m², and 851.5 g C/m² for the Nicasio Blend, Hi-Test, and Vermicompost, respectively. We also included a control treatment consisting of unamended soil. Five jars per treatment and the control were used for greenhouse gas (GHG) measurements for carbon dioxide (CO₂), nitrous oxide (N₂O), and methane (CH₄). An additional 76 jars of treatment and control soils were prepped for destructive sampling (n = 3 per treatment/control and sampling period). The destructive jars were used for determination of soil pH, gravimetric water content (GWC), and ammonium (NH₄⁺) and nitrate (NO₃⁻) concentrations throughout the incubation experiment and treated exactly as the gas measurement jars. Wet-up events from early season rainfall

can be characterized by short-term pulses of N₂O emissions and may account for a high proportion of the annual flux (Ryals and Silver 2013); thus, water was applied to incubation jars after the first week to simulate a wet-up event. Total C and N concentrations in the soil were analyzed before incubation and at the end of the six-week experiment. The destructive samples were collected once per week immediately following GHG measurements for weeks 1-4 and a final sample in week 6.

The incubation jars were stored in the dark at 25°C. During the first week of the incubation the soils were kept at field-moisture, and the accumulation of N₂O, CO₂, and CH₄ was collected from the headspace and stored in over-pressurized 20 mL, pre-evacuated glass vials crimped with rubber septa. Once gas samples were taken, the jars were opened and left to vent for 5 minutes, resealed, and a time zero gas sample was immediately collected from the jars and stored in the vials. Laboratory air was injected into the gas incubation jars to maintain pressure. The destructive jars were also opened and left to vent for 5 minutes then resealed. After the first week, all the jars were brought to field capacity simulating a wet-up rain event. Once water was added to all the jars, the total mass of sealed jars was recorded and maintained weekly to achieve constant moisture content throughout the rest of the experiment. Gas flux measurements are reported for days 1-9, 16, 21, 28, 30, 35, 37, and 42. Gas samples were analyzed on a Shimadzu GC-14A gas chromatograph with an electron capture detector for N₂O, a thermal conductivity detector for CO₂, and a flame ionization detector for CH₄ (Shimadzu Scientific Inc., Columbia, Maryland, USA). Nine samples (of 144 total) were removed due to bad injections.

The second incubation experiment tested the biogeochemical effects of one compost type across four rangeland soils that differed in chemical and physical properties. Soils were collected from Nicasio Native Grass Ranch at two locations including WR 5 described above for experiment 1 and WR 6 described in Ryals et al. (2014). The WR 6 site had a higher sand content (54%) and lower clay content (12%) than the WR 5 soils (Ryals et al. 2014). The third soil was collected from a grassland located in Tomales, CA, hereafter referred to as Tomales 1. These soils are classified in the Blucher-Cole series as Haploxerolls and Argixerolls great groups and are derived from sandstone, granite and shale (Beaudette and O'Geen, 2009). Soil texture analyses were conducted with the hydrometer method (Gee and Bauder, 1986) yielding clay, silt, and sand concentrations of $1 \pm 1\%$, $32 \pm 2\%$, and $66 \pm 2\%$, respectively. The last set of soils was collected from a second grassland in Tomales, hereafter referred to as Tomales 2 and are classified in the Tomales-Steinbeck series as Argixerolls and Haploxerolls great groups and are derived from weathered sandstone (Beaudette and O'Geen, 2009). Soil texture, determined as above, consisted of $7 \pm 1\%$ clay, $29 \pm 3\%$ silt, and $64 \pm 3\%$ sand (Gee and Bauder, 1986). All soils were collected in March 2024.

The Nicasio Blend compost from West Marin Compost, CA, was applied to 200 g of field-moist soil at a rate of 65.5 g N/m². Unamended soils served as the control treatment. There was a total of 40 jars that were reported for GHG fluxes ($n = 5$ per treatment, days 1, 3, 4, 5, 6, 7, 9, 12, 16, 19, 23, and 26, total $n = 480$), and an additional 160 jars were used for destructive sampling for soil measurements ($n = 5$ per

week and treatment). These jars were used for soil pH, GWC, and NH_4^+ and NO_3^- analyses throughout the incubation experiment and treated exactly as the GHG measurement jars. The jars used for destructive sampling were collected once a week at the end of weeks 1, 2, 3, and 4. The incubation jars were stored in the dark at 25°C. Mass (jar plus soil) was monitored weekly and moisture content adjusted to maintain levels. Gas samples were stored in over-pressurized 20 mL, pre-evacuated, glass vials crimped with rubber septa. Once gases were taken, the jars were opened and left to vent for 5 minutes. Once resealed, a gas sample was immediately collected from the jars and stored in the vials. Atmospheric air from the laboratory was injected into the gas incubation jars after the time zero sampling to maintain pressure. The destructive jars were also opened and left to vent for 5 minutes then resealed.

Literature Review

The literature review focused on compost application to agricultural fields that measured GHGs, in particular N_2O emissions. Keywords that were used to search for articles included compost, agriculture, and N_2O . We focused on compost applications that were not mixed with inorganic fertilizers and that had information regarding the compost applied including the C and N concentrations and feedstock composition of the compost.

Statistical Analysis

In the first incubation experiment, gas measurements were analyzed using a two-way repeated measures Analysis of Variance (ANOVA) with treatment and day as factors. Incubation 2 data were analyzed using a three-way repeated measures ANOVA with treatment, site, and day as factors. Soil NH_4^+ and NO_3^- , pH, and GWC data were analyzed using a two-way repeated measures ANOVA with treatment and week as factors. Total C and N data were analyzed with a one-way ANOVA to determine significant differences between treatments, where pre-incubated soil was treated as a treatment. Interactions were analyzed using Tukey's Multiple Comparisons Post Hoc test. Correlations for the metanalysis were determined using Pearson's product moment correlations statistics. All analyses were tested for normality using the Shapiro-Wilk test. Heteroscedasticity was analyzed by plotting residuals on a qq-plot. Data were log-transformed if necessary to meet the assumptions of ANOVA. Statistical analyses were performed using R Studio 4.3.0. Significance was determined as $p < 0.05$ unless otherwise noted.

Modeling

Compost effects on soil C and N for 0-30 cm depth, biomass C and N, and soil N_2O and CO_2 emissions were calibrated (e.g., adjusted to match a set of test data) and validated (e.g., tested against an independent set of data) using field studies across California (Table 2). There were four types of compost in the studies that were used in this modeling work: green waste with a C:N ratio of 11, 16, and 18, and food waste with a C:N ratio of 16, applied at rates of 550-1420 g C/m² one to three times (Ryals & Silver,

2013; Ryals, et al., 2014 and 2016; Mayer & Silver, 2022; Fenster et al., 2023; Anthony et al., 2024).

The findings of the lab experiment were taken into consideration for parameter selection and value range for calibration. Parameters regarding compost C pool allocations to surface and soil pools (e.g., slow surface vs. slow soil pools), along with the decomposition of these pools, nitrification rate, and additional parameters governing crop life cycle (Table 3) were simultaneously calibrated using a Bayesian method with Markov Chain-Monte Carlo (i.e., DiffeRential Evolution Adaptive Metropolis) to estimate parameter distributions and determine an optimal parameter set (Zhang et al., 2020). The Bayesian calibration was conducted numerous times with different sets of parameters and value ranges to ensure the results were as consistent and optimal as possible. Note that the model was calibrated for field settings, which differ from the lab environments.

Results and Discussion

Effects of different compost types

Overall, there were no statistically significant effects of compost type on mean N₂O emissions and emissions of N₂O were generally low apart from a few high flux events following wet-up (Figures 1 and A1). Vermicompost resulted in greater variability in N₂O fluxes. Soil GHG emissions remained very low during the first week of the experiment due to the dry soil conditions (Figure A1). Water addition led to a sharp increase in CO₂ and N₂O emissions, similar to patterns observed in the field (Ryals and Silver 2013). Wet-up events stimulated microbial respiration and N₂O production via nitrification and denitrification (Barnard et al., 2015; Hungate et al., 1997). The vermicompost-amended soils exhibited significantly higher N₂O emissions immediately after water was added (all $p < 0.001$), likely due to greater N availability and the lower C:N ratio (Figure A1).

Soil CH₄ emissions were low overall, except in the vermicompost which had significantly higher CH₄ emissions than the other treatments (Figure 1). Soil CH₄ emissions increased toward the end of the incubation experiment in the vermicompost-treated soils (Figure A1). The vermicompost consisted of earthworm castings, which have passed through the earthworm gut potentially inoculating soils with CH₄ producing archaea (Lubbers et al., 2013). This process likely explains the increase in CH₄ emissions observed compared to the other treatments. The vermicompost had higher average CH₄ emissions but also had higher nutrient content presenting a tradeoff for producers.

The vermicompost treatment had a significantly higher initial mean NO₃⁻ concentration (41 ± 7 mg/kg soil) compared to other treatments following the addition of water that quickly decreased after water addition (Table 4). The increase in soil moisture likely stimulated NO₃⁻ production and associated N₂O emissions via nitrification and/or denitrification. The initially higher NO₃⁻ levels observed in soils amended with vermicompost may be attributed to its lower C:N ratio and the greater N availability

within the compost. The Nicasio Blend, Hi-Test, and the control treatments had similar NO_3^- concentrations throughout the incubation. Soil NH_4^+ concentrations fluctuated over the course of the experiment but did not follow a significant trend over time or across treatments.

The Hi-Test amended soils retained more C by the end of the experiment than the other treatments, although the amount of C loss from all the compost treatments was relatively low (Figure 2). The average change in total C from pre-incubated soils to the final sampling point was -0.6 ± 1.8 g/kg for the Hi-Test treatment; -3.7 ± 1.5 g/kg for the Nicasio Blend; -2.9 ± 2.4 g/kg for the vermicompost, and -7.9 ± 1.0 g/kg for the control treatment. Some C loss is expected due to microbial C respiration of soils and added organic material. The Hi-Test amended soils had significantly higher soil C concentrations than all other treatments in week 6 (Figure 2). Among the three composts, the Hi-Test compost had the second-highest initial C:N ratio and 141.3 ± 4.3 g/kg total C compared to the Nicasio Blend with 243.8 ± 8.9 C g/kg and the vermicompost with 82.6 ± 3.1 C g/kg.

Following the addition of water, soil pH was significantly different in week 1 relative to the remaining weeks in the experiment across all treatments (all $p < 0.001$; Figure 3). Soil pH exhibited a similar pattern over time across treatments with an increase in soil pH observed between weeks 2 and 4, followed by a subsequent decrease during weeks 5 and 6 (Figure 3). As decomposition progresses, the breakdown of organic matter releases organic acids and hydrogen ions, contributing to a subsequent decline in soil pH; nitrification could have also contributed to soil pH decline over time (Bloom et al., 2005). Soil N_2O emissions tend to be higher in acidic soils below pH 6.7 (Wang et al., 2018). In this study, lower pH and higher N_2O emissions occurred early in the study (Figure A1 and Figure 3).

Effects of compost on different soils

In the second incubation experiment, soil amendments to moist soils significantly increased average N_2O emissions from soils at all sites (Figure 4). The average increase in N_2O emissions was 8.23 ± 2.07 ng N_2O g $^{-1}$ d $^{-1}$ with amendment and was highest in the WR 5 soil and the lowest from the Tomales 1 soil. Soil N_2O emissions in experiment 2 were generally lower than in experiment 1 but were sustained over time in both treatment and control soils. Soil N_2O emissions in the amended soils declined to levels comparable to the unamended control as the experiment progressed (Figures 4 and A2).

Compared to the controls, amended soils emitted more N_2O during days 1-6 for Tomales 1 and 2 and WR 6 (all $p < 0.001$), and until day 4 at WR 5 ($p < 0.001$) (Figure A2). Soils from WR 6, Tomales 1, and Tomales 2 were sandy loams while WR 6 had a coarser loamy sand texture. In coarser soil textures, N_2O may be favored by NH_4^+ oxidation, although denitrification can also occur (Zhu-Barker et al., 2015). The soils from WR 6 experienced negative N_2O emissions on day 5 in the unamended soil ($p < 0.05$). Uptake of N_2O is influenced by soil NO_3^- availability (Senbayram et al., 2012),

which at the end of week 1 was low in the unamended soil (0.23 ± 0.02 mg/kg) compared to the amended soil (5.45 ± 0.80 mg/kg) for the WR 6 site (Table 5). The WR 6 soils exhibited the greatest difference in N_2O emissions between amended and unamended treatments and had the lowest initial total soil C (8.37 ± 0.83 g/kg) and N (0.73 ± 0.01 g/kg) concentrations. The increased N_2O emissions during the first days after compost application were likely due to enhanced denitrification of soil NO_3^- from the addition of easily decomposable substrates (Velthof et al., 2003). Soils with low initial C and N concentrations may respond strongly to increased C and N availability, which can stimulate microbial activity (Jackson et al., 2017; Ryals and Silver, 2013; Zhu-Barker, 2023). The amended soils had higher CO_2 emissions throughout the incubation experiment (Figure 3). The increase in CO_2 emissions observed toward the end of the experiment in the amended soils across all sites suggests that the compost amendment supported microbial activity (Ryals et al., 2014). No treatment effects were observed in CH_4 emissions (Figure 3).

Soil NO_3^- concentrations exhibited an increasing trend over the course of the incubation period, suggesting that the compost functioned as a slow-release fertilizer (Ryals et al., 2014). The incubations took place in the absence of plants; the presence of plant roots could mediate the increase in NO_3^- concentrations and further lower N_2O emissions. Soil NH_4^+ did not vary significantly across treatments during the incubation experiment (Table 5), and nitrification may have occurred rapidly in the absence of plant uptake (Stark and Hart 1997).

Total C and N concentrations trended higher in the compost-amended soils but the differences were not significant at the end of the experiment; there was considerable variability in the data making it difficult to detect statistically significant trends (Figure 5). Some of the labile forms of C may have been consumed early in the experiment contributing to variability (Liyanage et al., 2022). Consistent with the results of the first incubation experiment, soil pH increased during weeks 2 and 3, followed by a decline in week 4, likely due to the decomposition of organic matter and associated production of organic acids and hydrogen ions (Figure 6). The amended soils had significantly higher pH than the unamended soils ($p < 0.05$). As in experiment 1, the effect of compost amendment on soil pH may help limit N_2O emissions.

Literature Review

A total of 29 studies examining the impacts of compost application on N_2O emissions in agricultural soils worldwide were compiled using the keywords compost, agriculture, and nitrous oxide (Table 6). Compost from the literature studies was mainly composted manure, composted green waste, food waste compost, or a mixture. We did not search for specific feedstocks or composting processes, although this will be added in future analyses. For example, this search criteria yielded no studies on vermicompost N_2O fluxes at the field scale.

Soil N₂O emissions averaged 14.6 ± 2 g N₂O-N ha⁻¹ d⁻¹ (n = 182) and ranged from 0.13 g N₂O-N ha⁻¹ d⁻¹ in a California grassland amended with green waste compost to 193.2 g N₂O-N ha⁻¹ d⁻¹ in an olive orchard amended with a green waste compost manure blend in Spain. The removal of six outliers (fluxes ≥ 100 g N₂O-N ha⁻¹ d⁻¹) lowered the average flux to 10.6 ± 1 g N₂O-N ha⁻¹ d⁻¹ (n = 176). There were no significant linear relationships observed between N₂O emissions and N application rate across studies (Figure 7). Production of N₂O is a product of complex interactions among factors such as soil moisture, temperature, redox potential, soil texture, soil pH, the decomposition of organic C, and mineral N availability (Firestone and Davidson 1989). Spatial variability within a field or landscape also may influence N₂O emissions and is less understood. Low-lying areas, historical land use legacies, and regions with high resource availability can serve as critical locations with elevated emission potential within the landscape (Anthony and Silver, 2024). A weak positive relationship was found between C:N ratio of composts used and N₂O emissions across all studies in the metanalysis (Figure 8; r = 0.23; p = 0.03). It is possible, and even likely, that the relationship between C:N ratio and N₂O dynamics is nonlinear across different ecosystems. It is also possible that not enough literature data were available to discern the shape of the relationship. Many studies have found that the C:N ratio can affect microbial community structure and consequently change the decomposition of organic C and N mineralization (Atoloye et al., 2024; Liang et al., 2017; Liyanage et al., 2022; Vaughan et al., 2011). The literature provides important data for model parameterization (e.g., range of compost qualities, soil types, climate zones) and validation (e.g., flux rates, soil C and N characteristics). The type of compost used in the studies may have also influenced N₂O emissions. In our literature review, compost types varied but some were more common than others (Figure 9). Green waste compost was among the most common in studies, comprised of yard waste or woody material or a combination of both. It is important to note that how composts are defined and classified varied across studies.

Modeling

The laboratory experiment results and the DayCent model testing prior to the Bayesian calibration underscored the necessity of allocating compost to both surface and soil pools at the outset, rather than starting only at surface pools. However, within the DayCent model's organic amendment input file, there exists the parameter only for surface pools' allocation. To address this limitation, we employed a parameter [CULTRA(6)] along with compost applications to account for the initial distribution of compost C and minerals between surface and soil pools. This new model adjustment facilitates consideration of soil pools in addition to surface pools from the initial distribution in DayCent. This option now allows a user to turn on amendment addition, or not. This workaround was an efficient and effective approach to improve model performance without the lengthy process of changing source code to establish a new model version that would require recursive model testing to avoid abnormal behaviors (e.g., Della Chiesa et al. 2022).

The Bayesian calibration further enhanced the model's performance. Results in the calibration showed a good model fit for top 30-cm soil C and N as well as for biomass C

and N, and soil N₂O and CO₂ emissions, with an Index of Agreement (IoA) greater than 0.75 (Figures 10-15). DayCent was able to simulate the general trend of N₂O emissions imposed by compost in the field, while N₂O emission simulations performed relatively weakly in the validation dataset, which was due to the high uncertainty in the observations (Figure 14). The impacts of compost on annual grassland N₂O emissions were highly variable among years (e.g., one high measurement from green waste; Figure 14B) and can be insignificant compared to the unamended control in the field (Anthony et al., 2024). Other variables achieved moderate to fair validation outcomes (IoA = 0.45 – 0.77). Notably, soil C and N simulations maintained minimal bias with 18%-25% errors. Compost applications can increase soil C and N annual accumulation rates compared to control sites (Figure 16). These trends were also captured by the DayCent simulations yet at a relatively lower magnitude.

The findings show that comprehensive calibration, incorporating measurements of multiple variables as well as key parameters such as initial allocations of compost C and minerals (Tables 2 and 3), improved the model performance and is crucial for accurately modeling the extensive impacts of composting on grasslands. Refining the DayCent model by including these key parameters and calibrating them with field data can capture C and N dynamics induced by compost applications in California annual grassland systems, with challenges remaining in modeling N₂O emissions.

To further enhance the accuracy of DayCent model predictions, future research should focus on collecting comprehensive, high-frequency time-series (daily to monthly) field data on more key variables, including soil NO₃, NH₄, moisture, and temperature. Incorporating abundant measurements of these key factors may improve the model's representation of nitrification and denitrification processes, thereby enhancing its ability to simulate N₂O emissions. Targeting CO₂ and N₂O separately could reduce the number of parameters for Bayesian calibration. Each parameter adds one more dimension (at least one more magnitude of possible choices) in the parameter space, making it more difficult to find the optimal set. Modeling CO₂ and N₂O separately may provide an interim solution to further improving model performance.

Conclusions

The goal of this project was to evaluate the functionality of the DayCent biogeochemical model for compost applications with special reference to N₂O emissions and develop approaches to improve model performance. Following the methodology outlined in this report, we conducted Bayesian calibration and validation of the DayCent model using field-study data from multiple rangeland sites in California. Calibration and validation yielded fair model performances, with substantial improvements in CO₂ emission (bias and error declined by over 29%) and reduced bias in N₂O emission simulations (by 40-117%) compared to default parameterization, although the error of N₂O emission simulations remained high. While the model performance improved for N₂O, to achieve greater accuracy in N₂O emission simulations, field research will be needed to further uncover the processes driving temporal N₂O high flux and inform future model updates.

Below, we summarize the key findings of the research and provide some recommendations for moving forward.

Key Findings

1. N₂O fluxes following compost amendments of different initial feedstocks and chemical quality were generally low. Vermicompost exhibited higher NO₃⁻ concentrations, hot moments of N₂O emissions, and more variable N₂O emissions.
2. Larger N₂O fluxes occurred shortly after a wet-up event in compost-amended soils, the control, and were particularly high in the vermicompost treatment. This highlights the pulse dynamics of this greenhouse gas. Significantly higher N₂O emissions following the wet-up event demonstrates the importance of capturing event-based fluxes.
3. Soils amended with vermicompost exhibited higher CH₄ emissions, likely driven by soil inoculation of methanogens from earthworm guts.
4. Compost application to soils collected during the wet season resulted in higher N₂O emissions relative to unamended soils. The emissions were generally low and decreased after the first one to two weeks.
5. The literature study provided an assessment of the range of compost properties, soil conditions, climate, and N₂O fluxes for agricultural sites. Relatively few data were available for rangelands. These data were used for model parameterization (environmental and compost variables) and validation (N₂O fluxes).
6. A Bayesian calibration approach, simultaneously targeting multiple biogeochemical variables (soil C and N, N₂O and CO₂ emissions, and biomass C and N), improved model performance for the prediction of those variables in the DayCent model.
7. Including key parameters in the Bayesian calibration, such as a parameter [CULTRA(6)] to account for the initial distribution among pools, improved DayCent model performance on carbon and nitrogen simulations for compost sites.
8. The high spatial and temporal variability typical of N₂O emissions makes them difficult to model with high accuracy. The laboratory, literature, and modeling research conducted as part of this contract improved model performance and identified future areas of potential improvement, particularly the need for more high-resolution N₂O flux data.

Recommendations

The findings from this research provide the most comprehensive assessment to date of mechanistic drivers and field flux data for compost amendments to rangeland soils. While we were able to improve the performance of the DayCent model, future work using continuous flux data is likely to provide the high resolution needed for the next generation of model improvements. The research yielded the following specific recommendations:

1. The high temporal variability of N_2O requires continuous flux data to make the next-generation improvements to biogeochemical modeling of N_2O . These types of data with detailed documentation should be incorporated into model development as they become available and are likely to greatly improve model performance.
2. Process-based models should develop specific parameters to account for the distribution of compost C and minerals within and between surface and soil pools to improve the compost representation in the model.
3. Vermicompost has the potential to increase CH_4 emissions, and possibly N_2O emissions after wet-up, from soils following application. The impacts of vermicompost should be followed in field studies and management adapted accordingly (e.g., avoid saturated soil conditions).

Figures and Tables

Table 1. Chemical compositions of composts used in the study. Values are means and standard errors.

Compost	C:N	C (g/kg)	N (g/kg)
Nicasio Blend	22	243.76 \pm 8.92	11.60 \pm 0.95
Hi-Test	17	141.28 \pm 4.26	6.31 \pm 0.11
Vermicompost	13	82.62 \pm 3.09	6.67 \pm 0.10

Table 2. Dataset used for DayCent calibration and validation. All targeting variables have data points from different treatments and studies for calibration and validation, except that there were not enough data from biomass N, and all of them were used for calibration.

Variables	Calibration		Validation	
	Annual/seasonal measurements	Treatments (Studies)	Annual/seasonal measurements	Treatments (Studies)
SOC	39	5 (3)	17	6 (2)
SON	39	5 (3)	17	6 (2)
Biomass C	103	5 (3)	15	3 (2)
Biomass N	16	1 (1)		
CO ₂	11	3 (1)	17	4 (3)
N ₂ O	15	4 (2)	13	3 (2)

Table 3. Optimal parameter values determined by Bayesian calibration.

Parameter name	Value	Lower bound	Upper bound	Definition
PRDX(1)	2.45	0.5	4.5	Coefficient for calculating potential above-ground monthly production as a function of solar radiation outside the atmosphere
FRTC(1), FRTC(2)	0.37	0.01	0.7	Fraction of C allocated to roots, with no water or nutrient stress
FRTC(4), FRTC(5)	0.34	0.01	0.7	Maximum increase in the fraction of C going to the roots due to water or nutrient stress
PRAMN(1,1)	9.00	5	40	Minimum C:N ratio with zero biomass
PRAMN(1,2)	30.76	15	70	Minimum C:N ratio with biomass greater than or equal to 200 g/m ²
PRAMX(1,1)	43.71	10	70	Maximum C:N ratio with zero biomass
PRAMX(1,2)	116.69	40	120	Maximum C:N ratio with biomass greater than or equal to 200 g/m ²

FSDETH(1), FSDETH(3), RDRJ, RDRM	0.25	0	0.7	Maximum monthly death rate of shoot, juvenile fine root, mature fine root
FALLRT	0.61	0	0.7	Standing dead monthly falling rate
FLGREM, FDGREM	0.17	0.01	0.8	Fraction of live shoots, standing dead removed by a grazing event
CULTRA(6)	0.03	0.01	1	Fraction of compost C and minerals (N, S, P) in topsoil pools at application
DEC5(1)	0.25	0.02	0.25	Maximum decomposition rate of surface slow C pool per year
DEC5(2)	0.13	0.02	0.25	Maximum decomposition rate of soil slow C pool per year
P2CO2(1)	0.67	0.4	0.7	Fraction of C loss as CO ₂ during decomposition from surface slow pool
P2CO2(2)	0.43	0.4	0.7	Fraction of C loss as CO ₂ during decomposition from soil slow pool
CKMRSPMX(2), CKMRSPMX(3)	0.25	0.01	0.9	Maximum juvenile or mature root fraction for maintenance respiration of root
CGRESP(2), CGRESP(3)	0.73	0.01	0.9	Maximum juvenile or mature root fraction for growth respiration of root
MAXNIT	0.70	0	1.5	maximum daily nitrification amount (g N/m ²)

Table 4. Weekly soil NO₃ and NH₄ concentrations (mg/kg soil) from incubated surface soils across treatments. Values are means and standard errors.

		Week				
		1	2	3	4	6
Treatment						
Control	NO ₃	0.13 ± 0.07	6.48 ± 0.87	2.73 ± 1.01	0.00 ± 0.00	0.68 ± 0.43
	NH ₄	3.26 ± 0.23	6.86 ± 0.33	1.36 ± 0.56	7.23 ± 3.93	1.04 ± 0.47
Nicasio Blend	NO ₃	5.97 ± 1.48	9.96 ± 2.01	6.11 ± 0.71	0.72 ± 0.39	0.00 ± 0.00
	NH ₄	3.61 ± 0.21	6.27 ± 1.02	1.18 ± 0.04	1.59 ± 0.29	0.28 ± 0.09
Hi-Test	NO ₃	2.75 ± 0.21	13.10 ± 0.19	3.75 ± 0.90	2.17 ± 0.16	0.26 ± 0.22
	NH ₄	8.54 ± 0.74	7.66 ± 0.27	1.56 ± 0.20	1.39 ± 0.47	4.79 ± 4.11
Vermicompost	NO ₃	41.34 ± 7.36 [*]	11.25 ± 1.94	4.80 ± 1.38	0.05 ± 0.05	0.00 ± 0.00
	NH ₄	3.88 ± 0.11	7.96 ± 0.20	5.46 ± 0.56	4.52 ± 1.26	1.24 ± 0.29

NO₃: Treatment (p < 0.001); Week (p < 0.001); Treatment: Week (p < 0.001),
NH₄: Treatment (p < 0.001); Week (p < 0.001); treatment: Week (p < 0.001).

Table 5. Soil NO₃ and NH₄ concentrations (mg/kg) in surface soils from four grasslands that were amended with compost for four weeks. Values are means and standard errors.

Site	Treatment		Week			
			1	2	3	4
Wick Ranch 5	Unamended	NO ₃	20.23 ± 0.53	55.28 ± 3.75	42.37 ± 3.08	68.84 ± 3.72
		NH ₄	0.14 ± 0.02	0.80 ± 0.08	0.05 ± 0.01	2.26 ± 1.46
	Amended	NO ₃	20.96 ± 2.14	41.70 ± 5.54	37.97 ± 2.90	60.09 ± 7.20
		NH ₄	0.25 ± 0.18	3.45 ± 2.60	0.05 ± 0.01	1.36 ± 0.26
Wick Ranch 6	Unamended	NO ₃	0.23 ± 0.02	2.51 ± 0.16	5.00 ± 0.24	11.84 ± 0.90
		NH ₄	0.05 ± 0.01	1.20 ± 0.13	0.12 ± 0.01	1.96 ± 0.25
	Amended	NO ₃	5.45 ± 0.80	9.61 ± 0.86	8.62 ± 0.98	13.91 ± 1.03
		NH ₄	0.54 ± 0.46	0.67 ± 0.05	0.08 ± 0.01	1.06 ± 0.10
Tomaes 1	Unamended	NO ₃	9.70 ± 0.14	16.53 ± 0.72	20.72 ± 85	24.51 ± 0.86
		NH ₄	0.04 ± 0.00	0.35 ± 0.07	0.03 ± 0.00	2.94 ± 2.56
	Amended	NO ₃	13.73 ± 0.53	19.07 ± 1.23	20.32 ± 0.76	21.19 ± 1.16
		NH ₄	0.03 ± 0.00	0.50 ± 0.08	0.03 ± 0.00	0.77 ± 0.14
Tomaes 2	Unamended	NO ₃	8.96 ± 0.68	12.50 ± 1.23	15.28 ± 0.91	23.37 ± 1.32
		NH ₄	0.03 ± 0.00	0.40 ± 0.08	0.04 ± 0.00	0.51 ± 0.03
	Amended	NO ₃	15.58 ± 0.63	18.31 ± 1.25	21.90 ± 1.53	21.44 ± 1.79
		NH ₄	0.05 ± 0.01	0.03 ± 0.03	0.04 ± 0.01	0.78 ± 0.26

NH₄: Treatment p = 0.98; Week p < 0.001; Site p < 0.001; treatment: Week p = 0.43; Treatment: Site p = 0.48; Week: Site p = 0.25; Treatment: Week: Site p = 0.42. NO₃ (all p < 0.001).

Table 6. List of articles that focused on compost applications and N₂O emissions.

#	Reference	Citation	Compost Type	Agricultural System
1	Ryals and Silver, 2013	Ryals, R., Silver, W.L., 2013. Effects of organic matter amendments on net primary productivity and greenhouse gas emissions in annual grasslands. <i>Ecol. Appl.</i> 23, 46–59. https://doi.org/10.1890/12-0620.1	Green Waste Compost	California
2	Kariyapperuma et al. 2011	Kariyapperuma, K.A., Furon, A., Wagner-Riddle, C., 2012. Nongrowing season nitrous oxide fluxes from an agricultural soil as affected by application of liquid and composted swine manure. <i>Can. J. Soil Sci.</i> 92, 315–327. https://doi.org/10.4141/cjss2011-059	Composted Manure	Canada
3	Ding et al. 2013	Ding, W., Luo, J., Li, J., Yu, H., Fan, J., Liu, D., 2013. Effect of long-term compost and inorganic fertilizer application on background N ₂ O and fertilizer-induced N ₂ O emissions from an intensively cultivated soil. <i>Sci. Total Environ., Soil as a Source & Sink for Greenhouse Gases</i> 465, 115–124. https://doi.org/10.1016/j.scitotenv.2012.11.020	Green Waste Compost	China
4	Ball et al. 2014	Ball, B.C., Griffiths, B.S., Topp, C.F.E., Wheatley, R., Walker, R.L., Rees, R.M., Watson, C.A., Gordon, H., Hallett, P.D., McKenzie, B.M., Nevison, I.M., 2014. Seasonal nitrous oxide emissions from field soils under reduced tillage, compost application or organic farming. <i>Agric. Ecosyst. Environ.</i> 189, 171–180. https://doi.org/10.1016/j.agee.2014.03.038	Green Waste Compost	Scotland
5	Suddick and Six, 2013	Suddick, E.C., Six, J., 2013. An estimation of annual nitrous oxide emissions and soil quality following the amendment of high-temperature walnut shell biochar and compost to a small-scale vegetable crop rotation. <i>Sci. Total Environ., Soil as a Source & Sink for Greenhouse Gases</i> 465, 298–307. https://doi.org/10.1016/j.scitotenv.2013.01.094	Green Waste Compost	California
6	Dalal et al. 2010	Dalal, R.C., Gibson, I., Allen, D.E., Menzies, N.W., 2010. Green waste compost reduces nitrous oxide emissions from feedlot manure applied to soil. <i>Agric. Ecosyst. Environ.</i> , Estimation of nitrous oxide emission from ecosystems and its mitigation technologies 136, 273–281. https://doi.org/10.1016/j.agee.2009.06.010	Green Waste Compost/ Composted Manure	Australia
7	Meijide et al. 2009	Meijide, A., García-Torres, L., Arce, A., Vallejo, A., 2009. Nitrogen oxide emissions affected by organic fertilization in a nonirrigated Mediterranean barley field. <i>Agric. Ecosyst.</i>	Green Waste Compost	Spain

		Environ. 132, 106–115. https://doi.org/10.1016/j.agee.2009.03.005		
8	Alluvione et al. 2010	Alluvione, F., Bertora, C., Zavattaro, L., Grignani, C., 2010. Nitrous Oxide and Carbon Dioxide Emissions Following Green Manure and Compost Fertilization in Corn. <i>Soil Sci. Soc. Am. J.</i> 74, 384–395. https://doi.org/10.2136/sssaj2009.0092	Green Waste Compost	Italy
9	Drury et al. 2014	Drury, C.F., Reynolds, W.D., Yang, X.M., Tan, C.S., Guo, X., McKenney, D.J., Fleming, R., Denholme, K., 2014. Influence of compost source on corn grain yields, nitrous oxide and carbon dioxide emissions in southwestern Ontario. <i>Can. J. Soil Sci.</i> 94, 347–355. https://doi.org/10.4141/cjss2013-077	Green Waste Compost	Canada
10	Ginting et al. 2003	Ginting, D., Kessavalou, A., Eghball, B., Doran, J.W., 2003. Greenhouse Gas Emissions and Soil Indicators Four Years after Manure and Compost Applications. <i>J. Environ. Qual.</i> 32, 23–32. https://doi.org/10.2134/jeq2003.2300	Composted Manure	Nebraska
11	Agegehu et al. 2016	Agegehu, G., Bass, A.M., Nelson, P.N., Bird, M.I., 2016. Benefits of biochar, compost and biochar compost for soil quality, maize yield and greenhouse gas emissions in a tropical agricultural soil. <i>Sci. Total Environ.</i> 543, 295–306.	Composted Manure	Australia
12	Kang et al. 2021	Kang, S.-W., Yun, J.-J., Park, J.-H., Cho, J.-S., 2021. Exploring Suitable Biochar Application Rates with Compost to Improve Upland Field Environment. <i>Agronomy</i> 11, 1136.	Green Waste Compost	South Korea
13	Bass et al. 2016	Bass, A.M., Bird, M.I., Kay, G., Muirhead, B., 2016. Soil properties, greenhouse gas emissions and crop yield under compost, biochar and co-composted biochar in two tropical agronomic systems. <i>Sci. Total Environ.</i> 550, 459–470. https://doi.org/10.1016/j.scitotenv.2016.01.143	Green Waste Compost/ Composted Manure	Australia
14	Ruangcharus et al. 2021	Ruangcharus, C., Kim, S.U., Yoo, G., Choi, E.-J., Kumar, S., Kang, N., Hong, C.O., 2021. Nitrous oxide emission and sweet potato yield in upland soil: Effects of different type and application rate of composted animal manures. <i>Environ. Pollut.</i> 279, 116892.	Green Waste Compost/ Composted Manure	South Korea
15	Takakai et al. 2019	Takakai, F., Kominami, Y., Ohno, S., Nagata, O., 2020. Effect of the long-term application of organic matter on soil carbon accumulation and GHG emissions from a rice paddy field in a cool-temperate region, Japan. -I. Comparison of rice straw and rice straw compost -. <i>Soil Sci. Plant Nutr.</i> 66, 84–95. https://doi.org/10.1080/00380768.2019.1609335	Green Waste Compost	Japan

16	Sánchez-García et al. 2016	Sánchez-García, M., Sánchez-Monedero, M.A., Roig, A., López-Cano, I., Moreno, B., Benitez, E., Cayuela, M.L., 2016. Compost vs. biochar amendment: a two-year field study evaluating soil C build-up and N dynamics in an organically managed olive crop. <i>Plant Soil</i> 408, 1–14. https://doi.org/10.1007/s11104-016-2794-4	Green Waste Compost/ Composted Manure	Spain
17	Wong et al. 2023	Wong, C.T.F., Falcone, M., Rich, G., Stubler, C., Malama, B., Lazcano, C., Decock, C., 2023. Short-term effects of increasing compost application rates on soil C and greenhouse gas (N ₂ O and CO ₂) emissions in a California central coast vineyard. <i>Front. Environ. Sci.</i> 11. https://doi.org/10.3389/fenvs.2023.1123510	Green Waste Compost/ Composted Manure	California
18	Sauer et al. 2009	Sauer, T.J., Compston, S.R., West, C.P., Hernandez-Ramirez, G., Gbur, E.E., Parkin, T.B., 2009. Nitrous oxide emissions from a bermudagrass pasture: Interseeded winter rye and poultry litter. <i>Soil Biol. Biochem.</i> 41, 1417–1424. https://doi.org/10.1016/j.soilbio.2009.03.019	Green Waste Compost/ Composted Manure	Arkansas
19	Trinh et al. 2017	Trinh, M.V., Tesfai, M., Borrell, A., Nagothu, U.S., Bui, T.P.L., Quynh, V.D., Thanh, L.Q., 2017. Effect of organic, inorganic and slow-release urea fertilisers on CH ₄ and N ₂ O emissions from rice paddy fields. <i>Paddy Water Environ.</i> 15, 317–330. https://doi.org/10.1007/s10333-016-0551-1	Green Waste Compost	Vietnam
20	Mukumbuta et al. 2017	Mukumbuta, I., Shimizu, M., Hatano, R., 2017. Mitigating Global Warming Potential and Greenhouse Gas Intensities by Applying Composted Manure in Cornfield: A 3-Year Field Study in an Andosol Soil. <i>Agriculture</i> 7, 13. https://doi.org/10.3390/agriculture7020013	Green Waste Compost/ Composted Manure	Japan
21	Thornton et al. 1998	Thornton, F.C., Shurpali, N.J., Bock, B.R., Reddy, K.C., 1998. N ₂ O and no emissions from poultry litter and urea applications to bermudagrass. <i>Atmos. Environ.</i> 32, 1623–1630. https://doi.org/10.1016/S1352-2310(97)00390-7	Composted Manure	Alabama
22	Badewa et al. 2022	Badewa, E.A., Yeung, C.C., Rezanezhad, F., Whalen, J.K., Oelbermann, M., 2022. Spring Freeze–Thaw Stimulates Greenhouse Gas Emissions From Agricultural Soil. <i>Front. Environ. Sci.</i> 10. https://doi.org/10.3389/fenvs.2022.909683	Composted Manure	Canada
23	Criscuoli et al. 2024	Criscuoli, I., Panzacchi, P., Tognetti, R., Petrillo, M., Zanutelli, D., Andreotti, C., Loesch, M., Raifer, B., Tonon, G., Ventura, M., 2024. Effects of woodchip biochar on temperature sensitivity of greenhouse gas emissions in amended soils within a mountain vineyard. <i>Geoderma Reg.</i> 38,	Food Waste Compost	Italy

		e00847. https://doi.org/10.1016/j.geodrs.2024.e00847		
24	Cai et al. 2013	Cai, Y., Ding, W., Luo, J., 2013. Nitrous oxide emissions from Chinese maize–wheat rotation systems: A 3-year field measurement. <i>Atmos. Environ.</i> 65, 112–122. https://doi.org/10.1016/j.atmosenv.2012.10.038	Green Waste Compost	China
25	de Rosa et al. 2016	De Rosa, D., Rowlings, D.W., Biala, J., Scheer, C., Basso, B., McGree, J., Grace, P.R., 2016. Effect of organic and mineral N fertilizers on N ₂ O emissions from an intensive vegetable rotation. <i>Biol. Fertil. Soils</i> 52, 895–908. https://doi.org/10.1007/s00374-016-1117-5	Green Waste Compost	Australia
26	Riches et al. 2016	Riches, D.A., Mattner, S.W., Davies, R., Porter, I.J., 2016. Mitigation of nitrous oxide emissions with nitrification inhibitors in temperate vegetable cropping in southern Australia. <i>Soil Res.</i> 54, 533–543. https://doi.org/10.1071/SR15320	Composted Manure	Australia
27	Pujol Pereira et al. 2016	Pereira, E.I.P., Suddick, E.C., Six, J., 2016. Carbon Abatement and Emissions Associated with the Gasification of Walnut Shells for Bioenergy and Biochar Production. <i>PLOS ONE</i> 11, e0150837. https://doi.org/10.1371/journal.pone.0150837	Composted Manure	California
28	CalRecycle, 2015	CalRecycle. Research to Evaluate Nitrous Oxide (N ₂ O) Emissions from Compost in Support of AB 32 Scoping Plan Composting Measure. 2015; Publication #DRRR 201500–1544. https://www2.calrecycle.ca.gov/Publications/Download/1183	Green Waste Compost	California
29	Anthony and Silver, 2024	Anthony, T.L., Silver, W.L., 2024. Hot spots and hot moments of greenhouse gas emissions in agricultural peatlands. <i>Biogeochemistry</i> 167, 461–477. https://doi.org/10.1007/s10533-023-01095-y	Green Waste Compost, Food Waste Compost	California

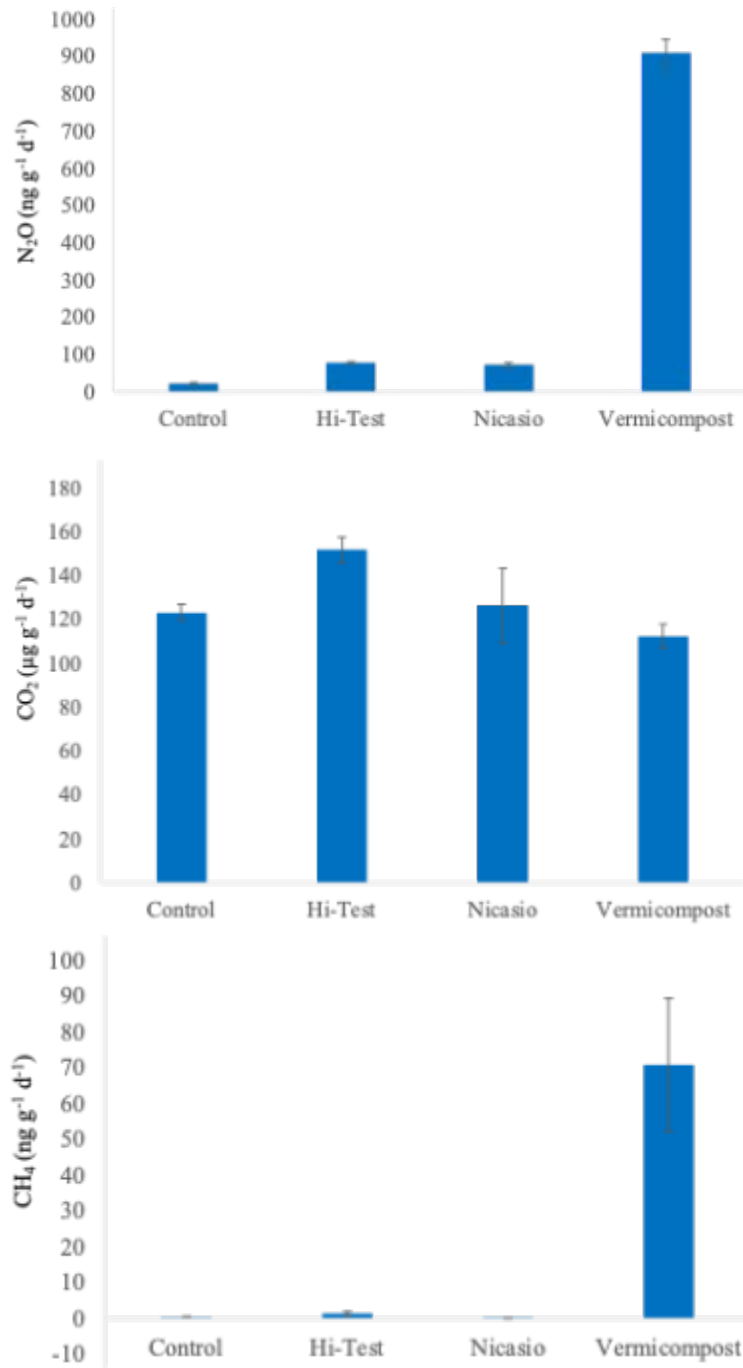


Figure 1: Mean (± standard errors) N₂O (top), CO₂ (middle), and CH₄ (bottom) emissions in soils amended with different composts and an unamended control. N₂O fluxes from the vermicompost were more variable than the other treatments, and there were no statistically significant treatment effects for N₂O emissions. Vermicompost had significantly higher CH₄ emissions than the other treatments or control.

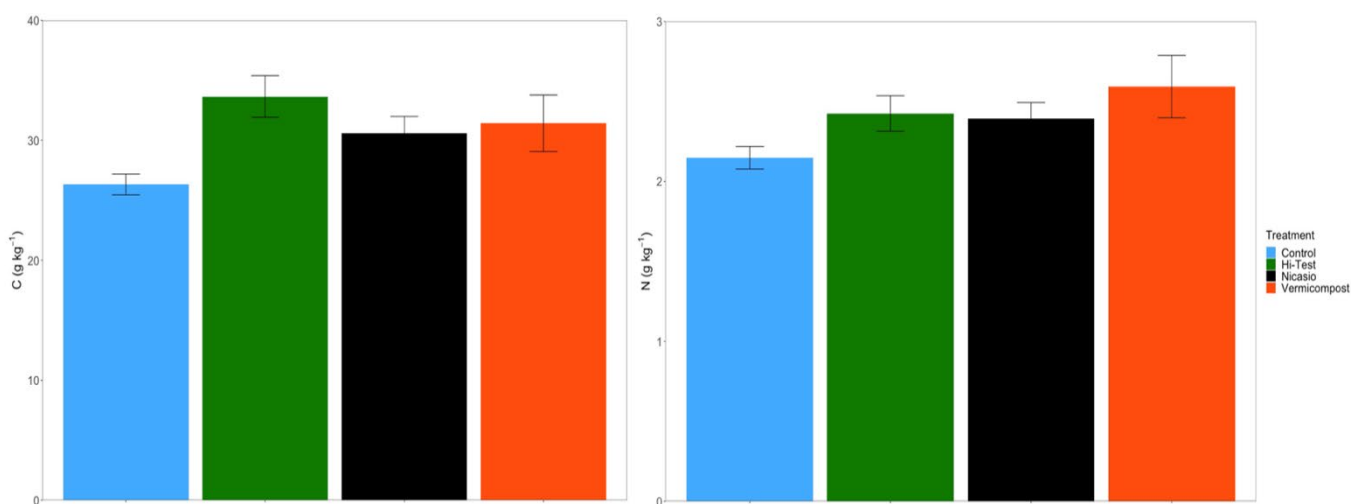


Figure 2: Mean soil C (left) and N (right) at the end of the six-week incubation. Error bars represent standard errors.

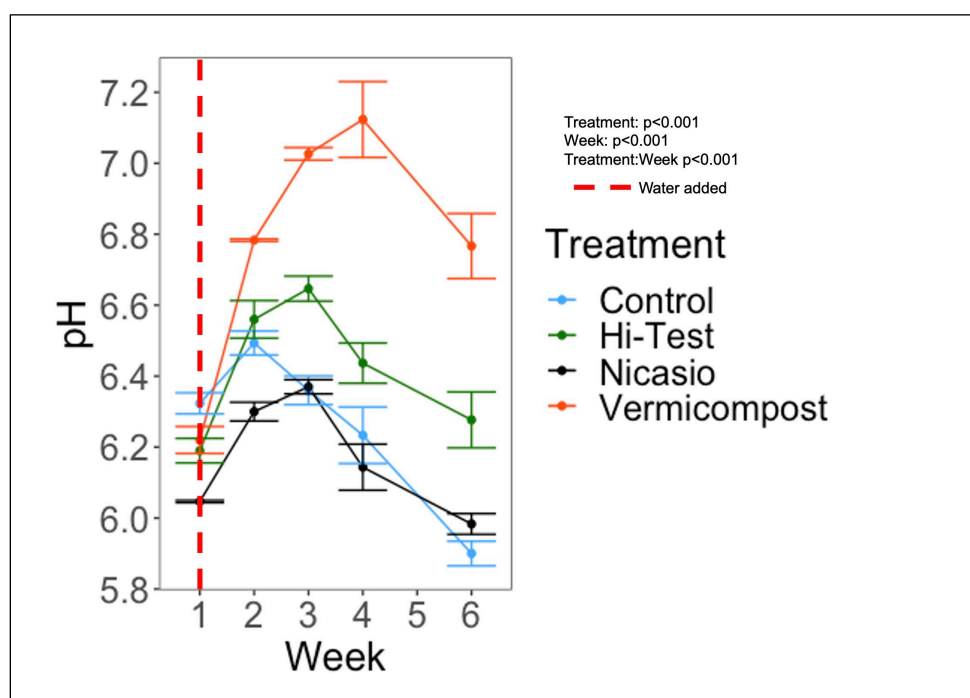


Figure 3: Weekly pH measurements in grassland soil amended with different compost types during a six-week incubation experiment. Red dotted line represents when water was added. Error bars represent standard errors.

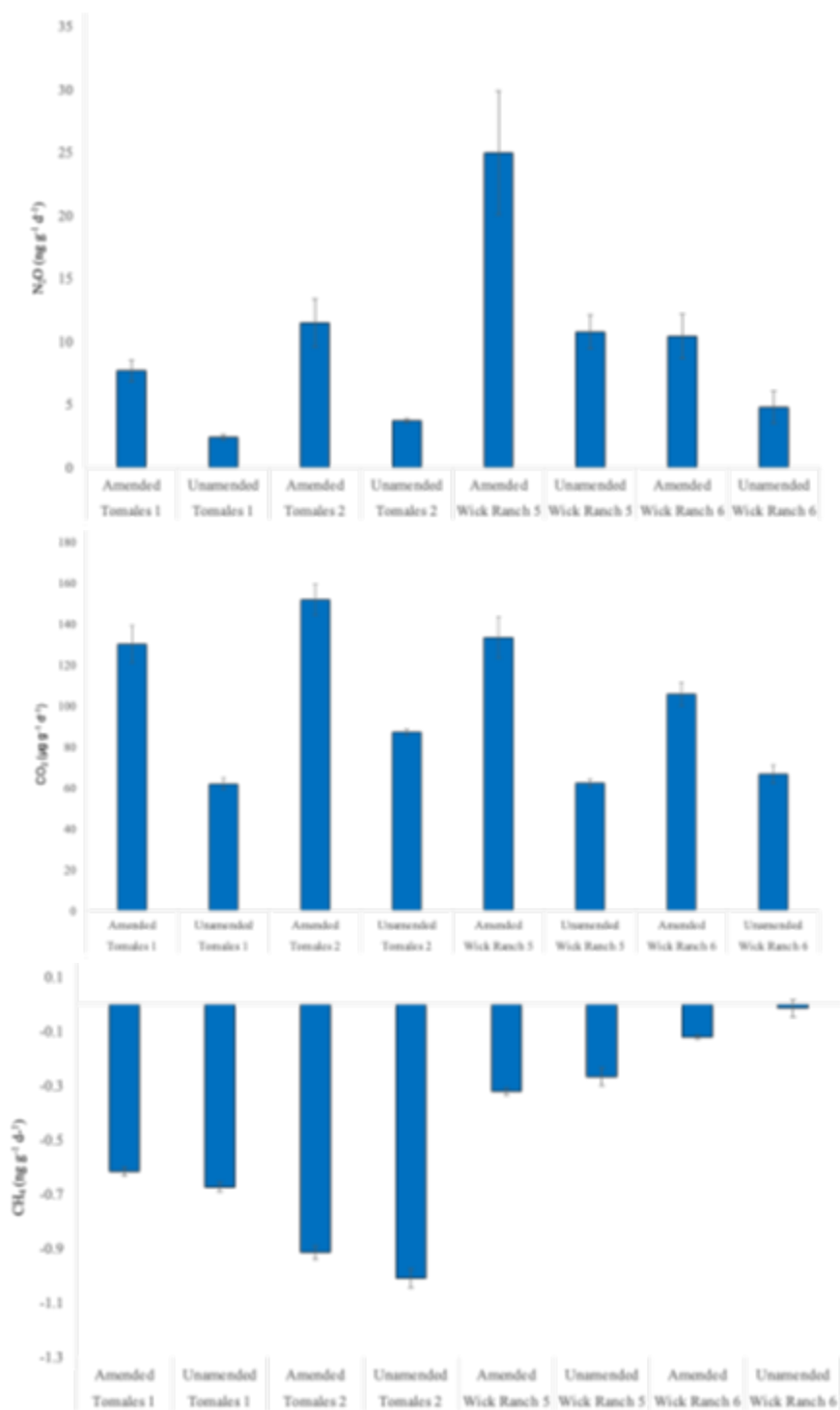


Figure 4. Greenhouse gas fluxes (means \pm standard errors) with and without compost addition to four different rangeland soils. Compost amendments significantly increase N₂O emissions relative to controls.

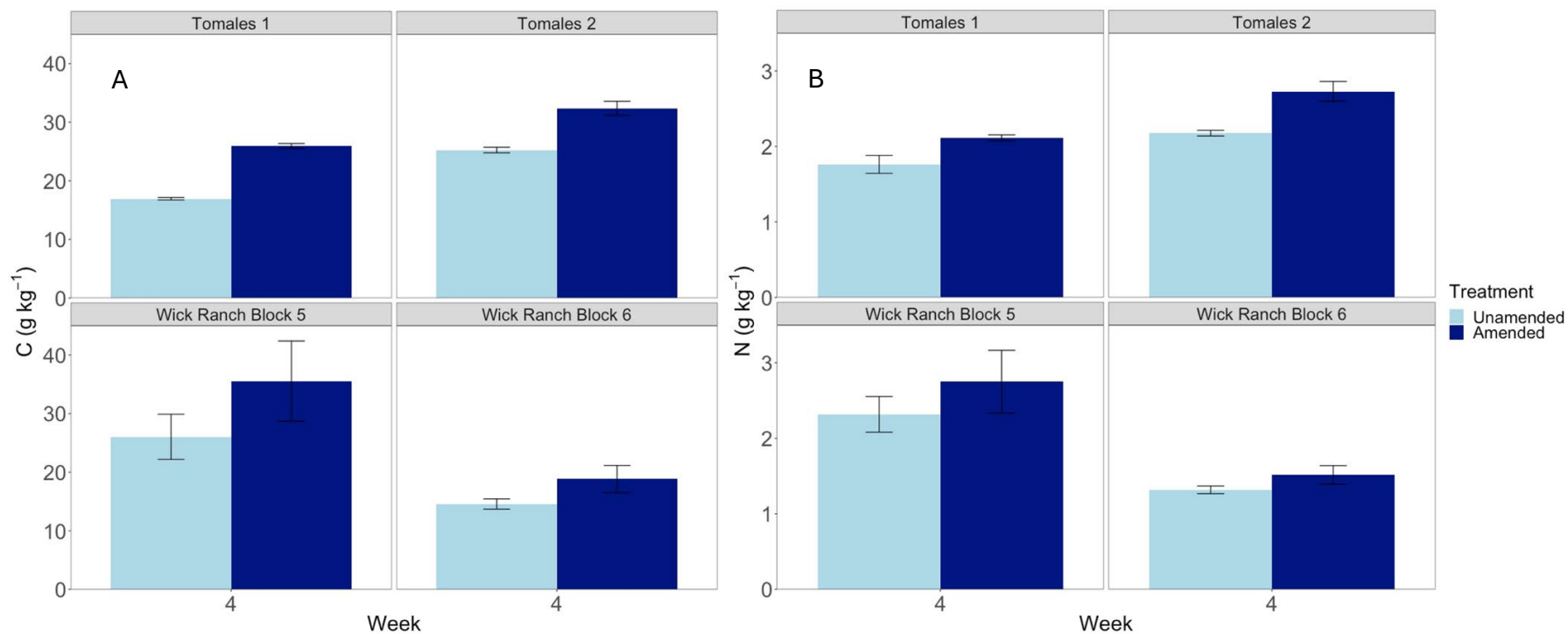


Figure 5: Total soil C (A) and N (B) following a four-week experiment where soils from four sites were amended with a compost and incubated for four weeks. Error bars are standard errors.

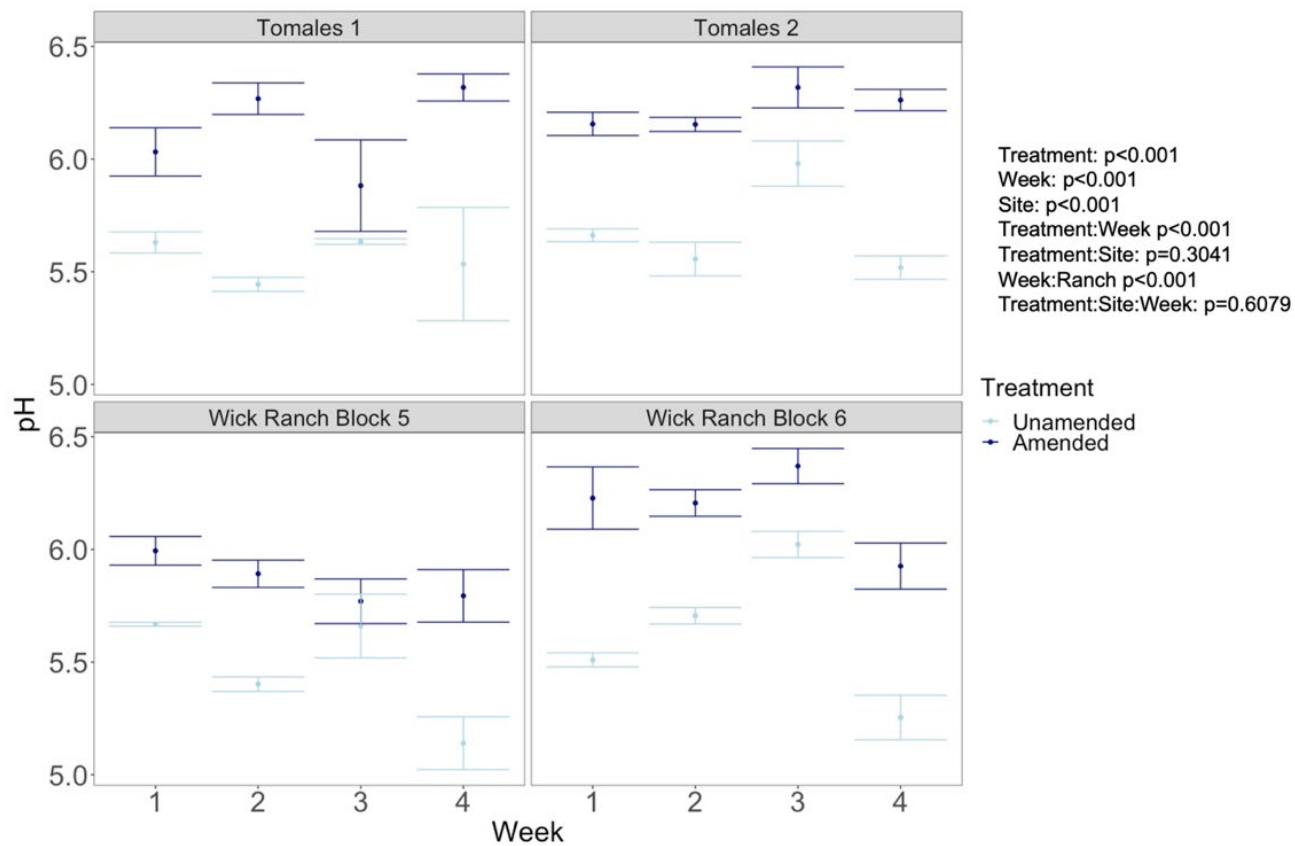


Figure 6. Soil pH (means \pm standard errors) with and without compost addition to four different rangeland soils. Amended soils had significantly higher soil pH which can help decrease N₂O emissions.

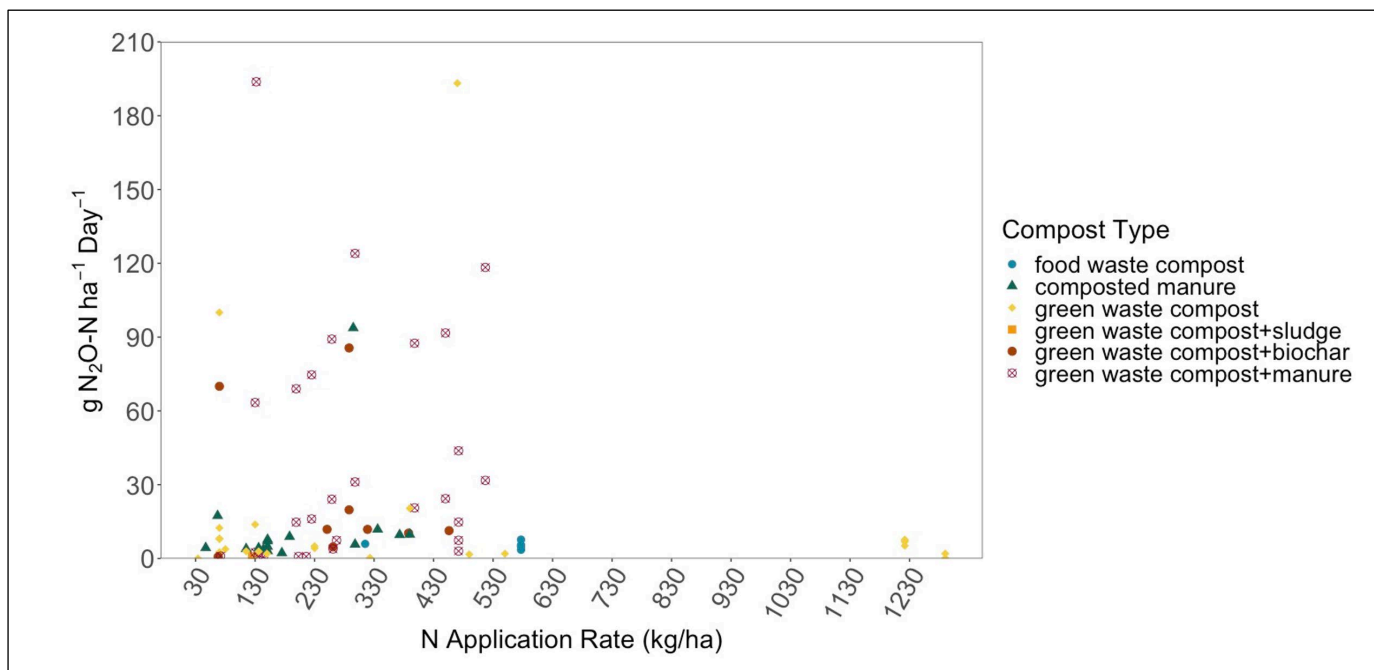


Figure 7. N₂O emissions in relation to N application rate from different composts. No strong relationship was found.

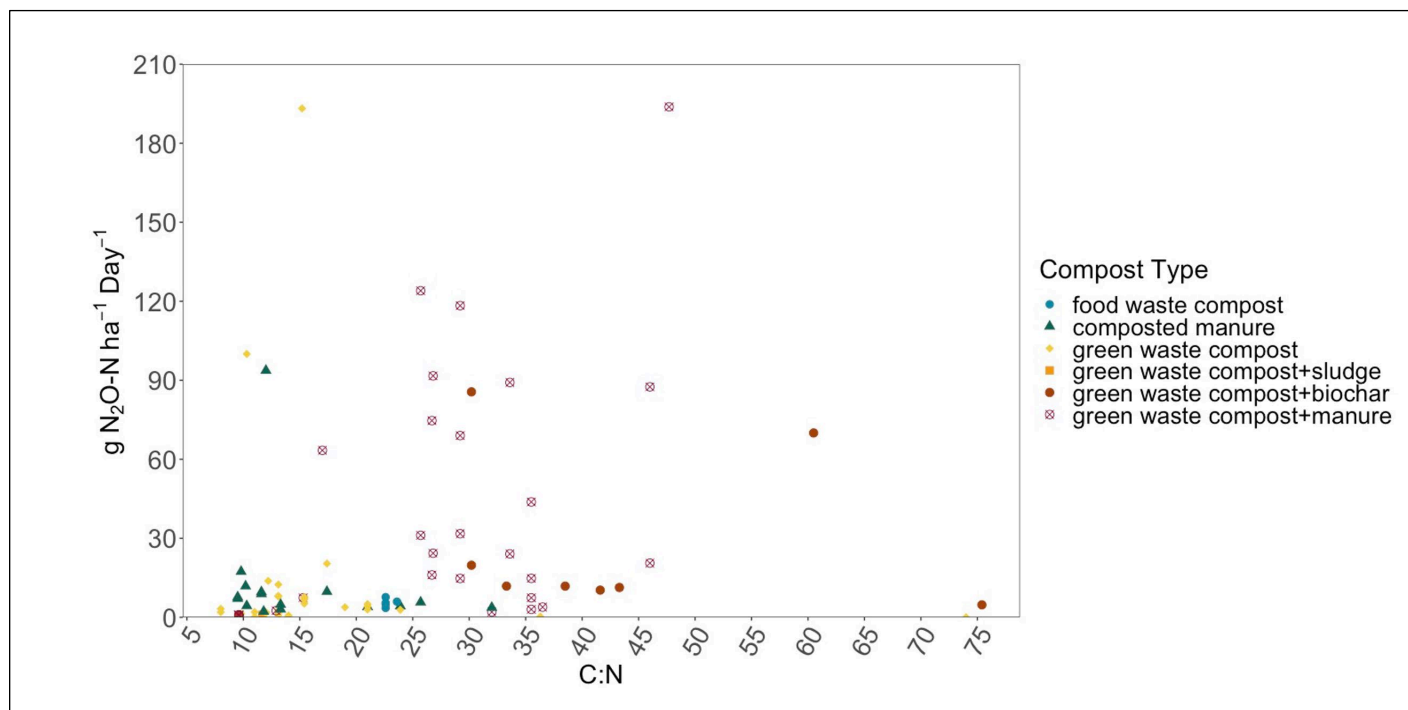


Figure 8. N₂O emissions versus C:N ratio of various composts in published studies. No strong relationships were found.

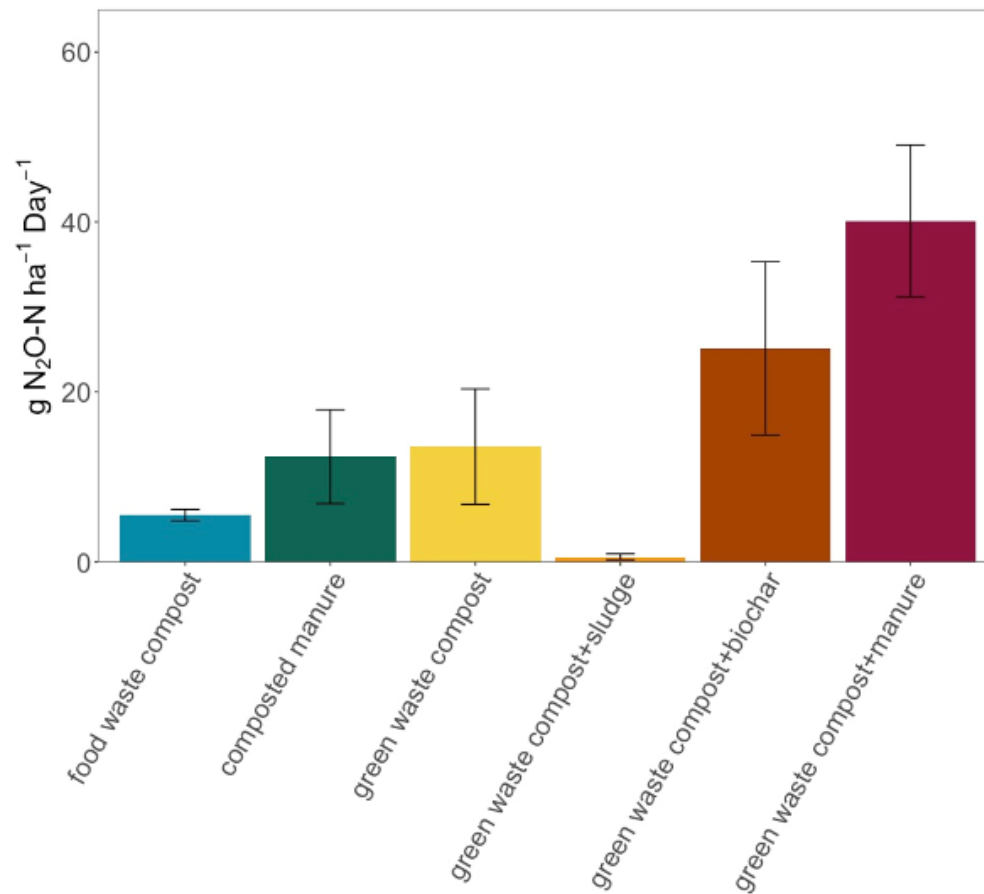


Figure 9. Compost type in relation to mean N_2O emissions across studies. Values on top of bars indicate number of studies. Error bars are standard errors.

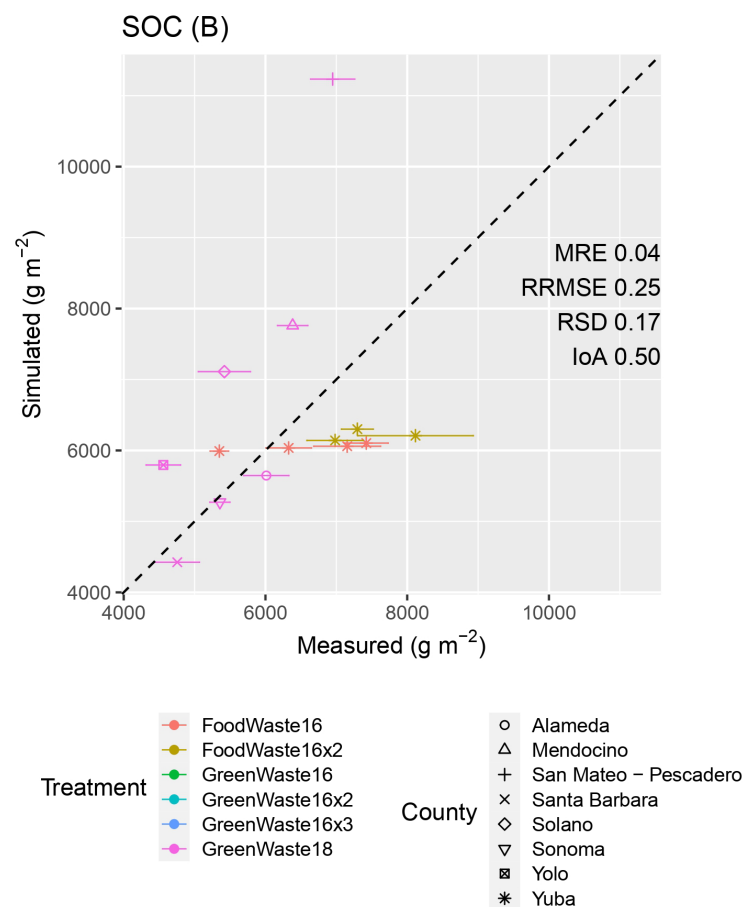
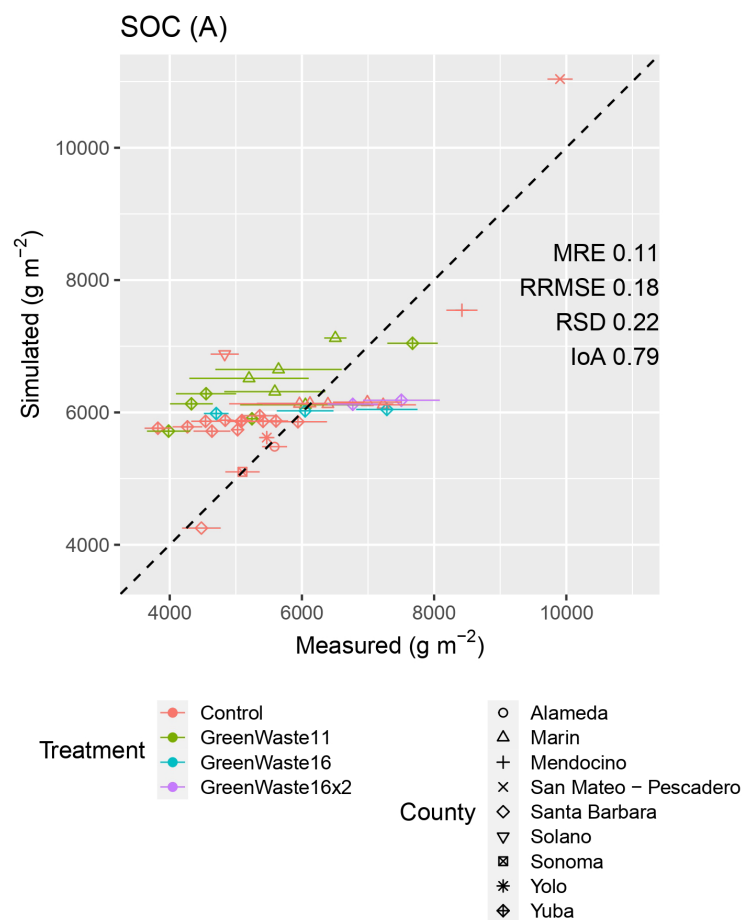


Figure 10. Calibration (A) and validation (B) of DayCent simulations on soil C in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment.

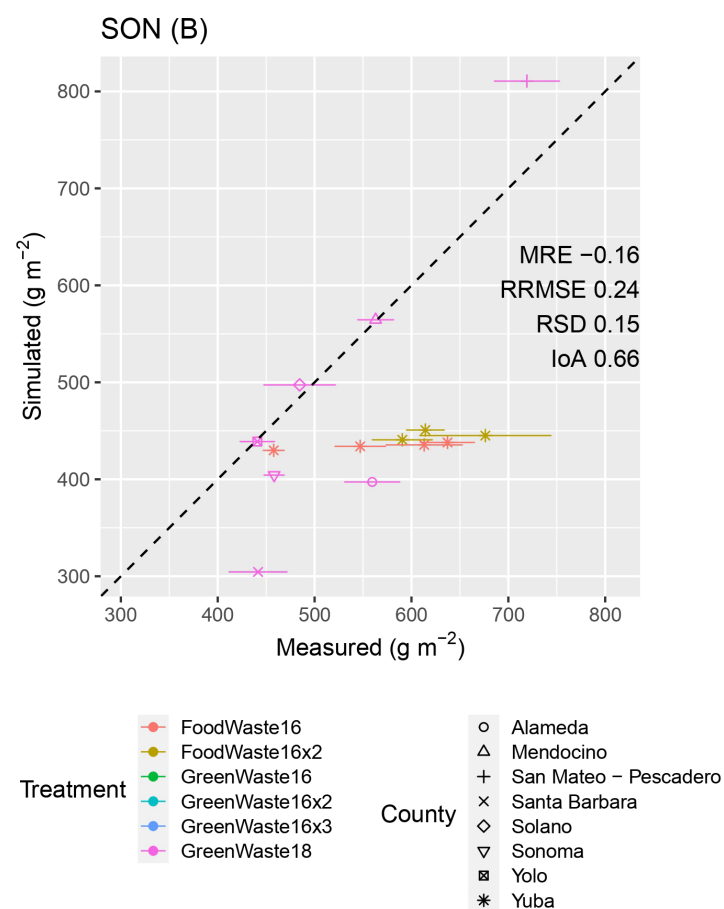
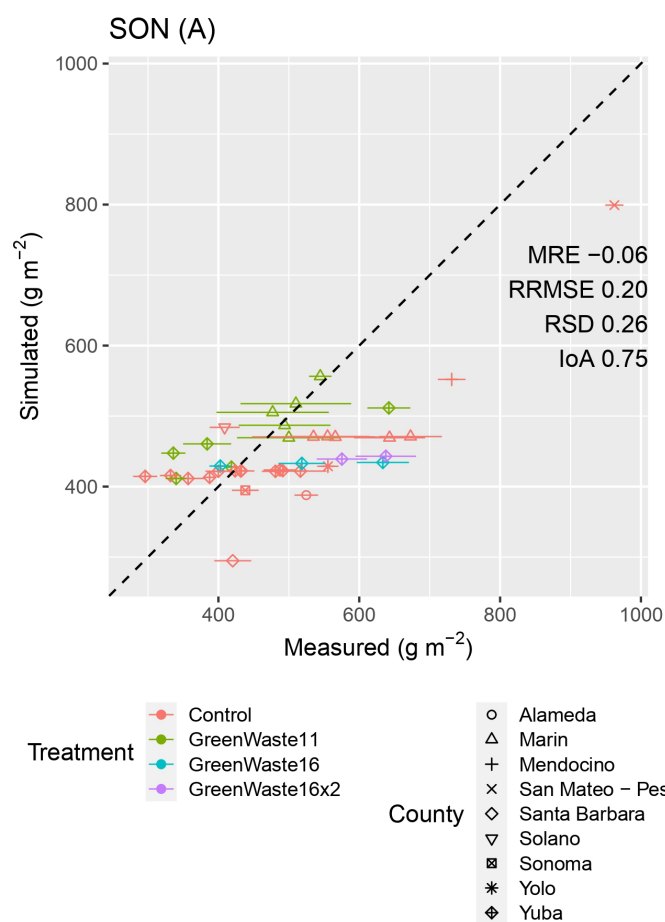


Figure 11. Calibration (A) and validation (B) of DayCent simulations on soil N in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment.

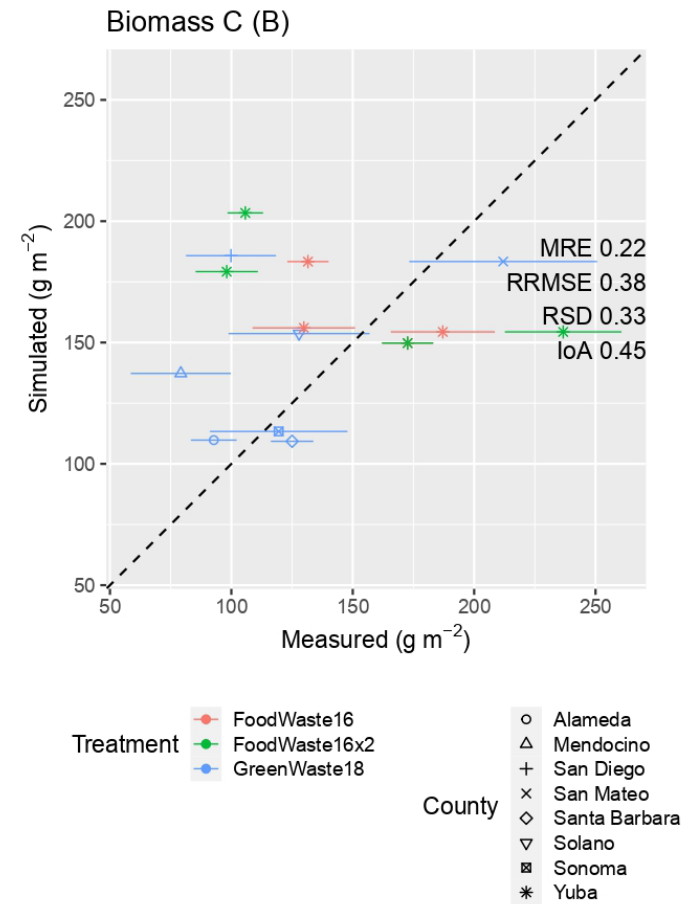
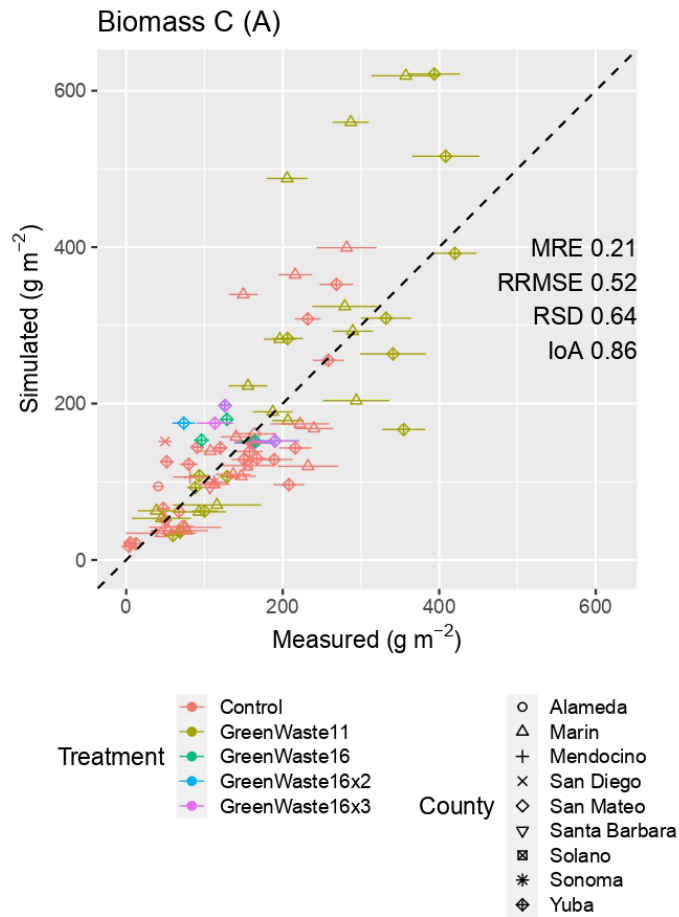


Figure 12. Calibration (A) and validation (B) of DayCent simulations on biomass C in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment.

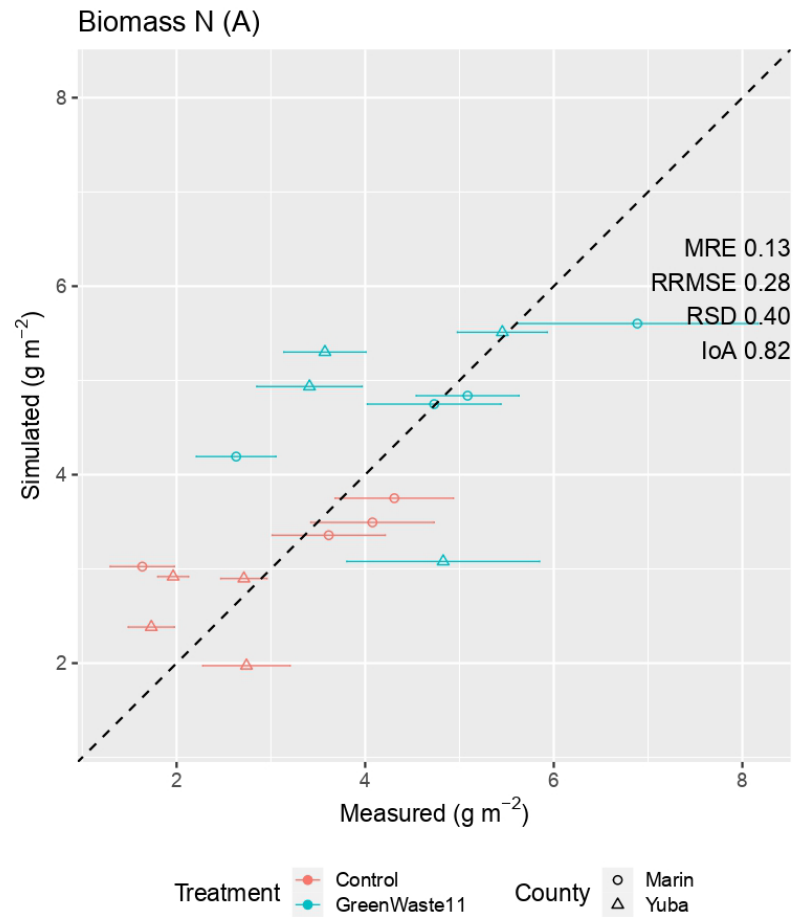


Figure 13. Calibration of DayCent simulations on biomass N in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment. Note that there was not enough data from biomass N, so all of them were used for calibration.

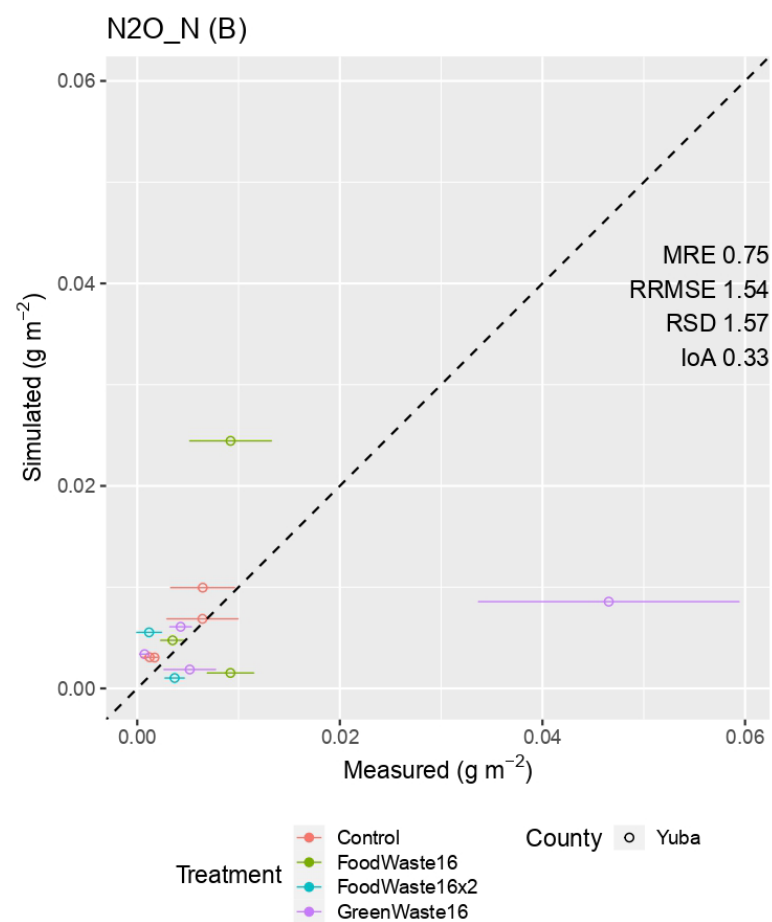
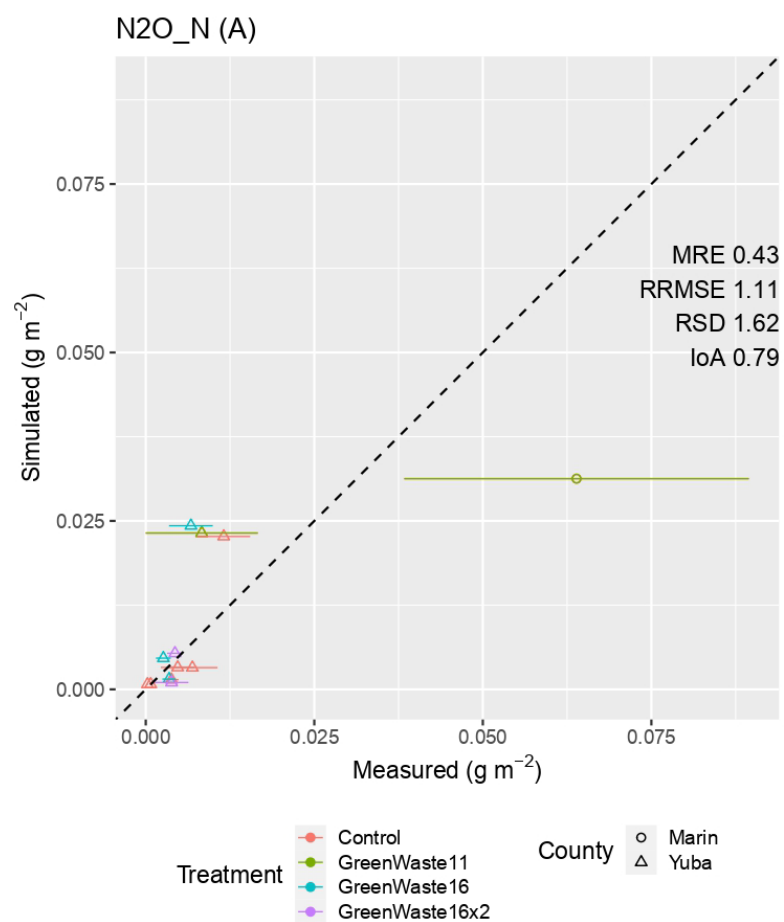


Figure 14. Calibration (A) and validation (B) of DayCent simulations on soil N_2O emissions in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment.

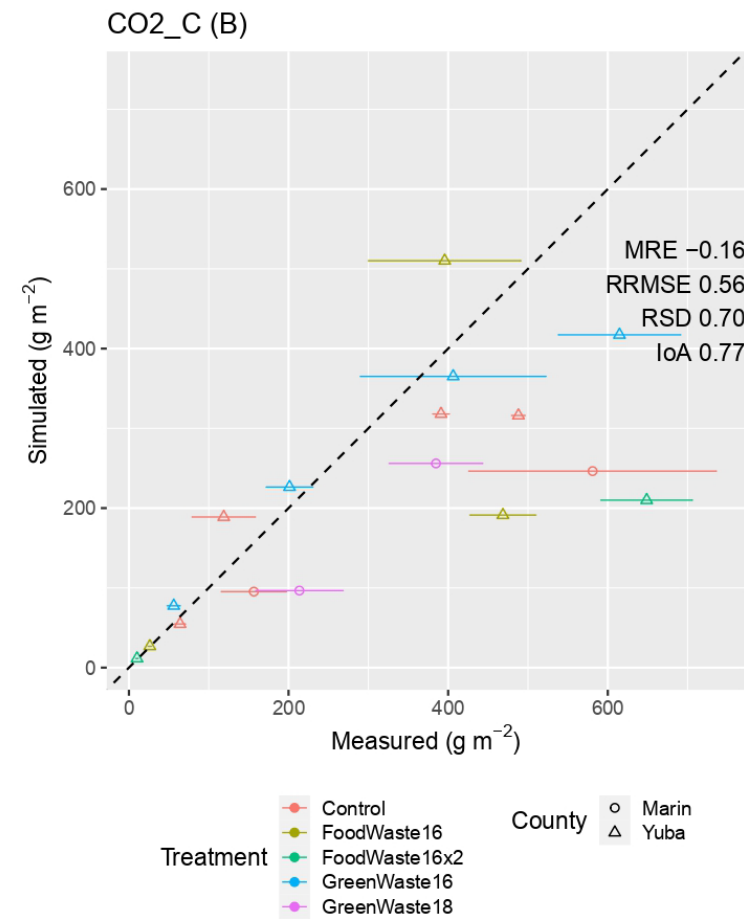
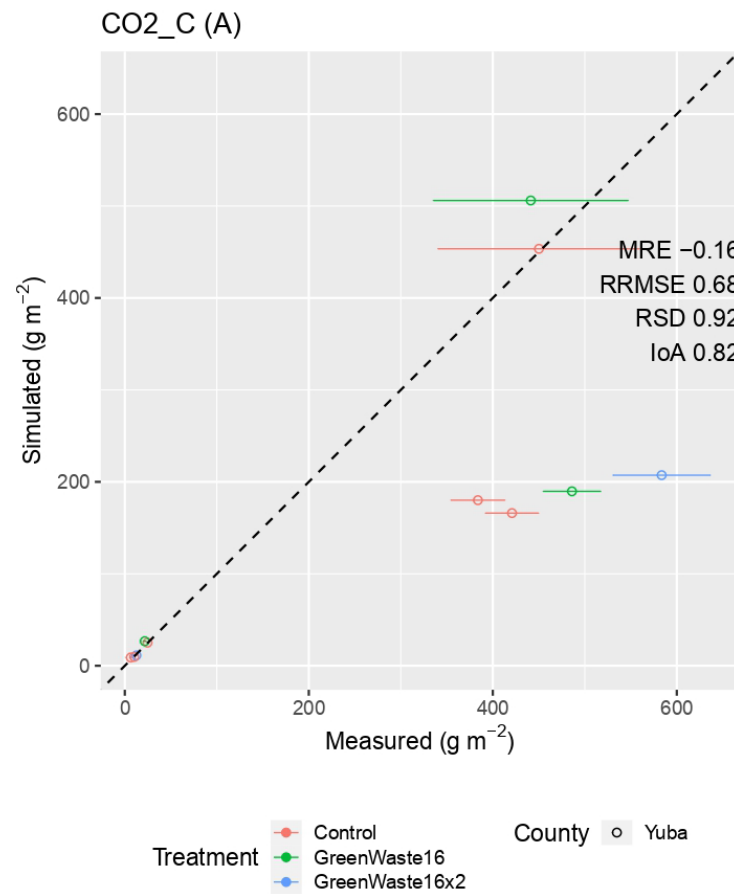


Figure 15. Calibration (A) and validation (B) of DayCent simulations on soil CO₂ emissions in California annual grassland. Simulations' mean relative error (MRE) and relative root mean square error (RRMSE), relative standard deviation of measurements (RSD), and Index of Agreement (IoA) are shown. A horizontal bar across a data point represents the measurement standard deviation of each treatment.

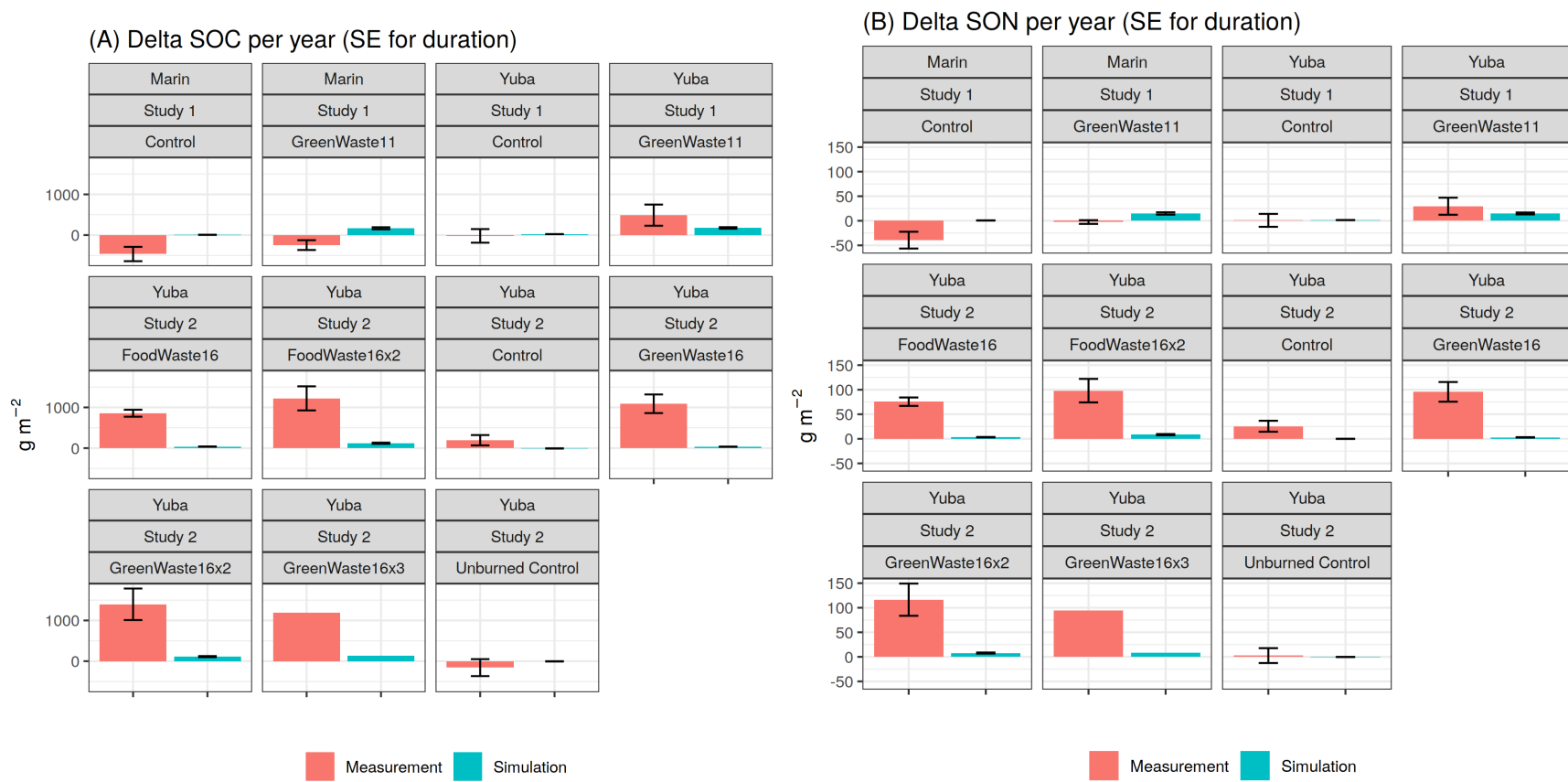


Figure 16. Annual changing rates of soil C (A) and N (B) in experimental sites of Marin and Yuba counties

Abbreviations and Acronyms

N₂O: nitrous oxide
CO₂: carbon dioxide
CH₄: methane
C: carbon
N: nitrogen
C:N: carbon to nitrogen ratio
GWC: gravimetric water content
NH₄⁺: ammonium
NO₃⁻: nitrate
GHG: greenhouse gas
g: grams
kg: kilograms
RRMSE: root mean square error
RSD: relative standard error
IOA: index of agreement

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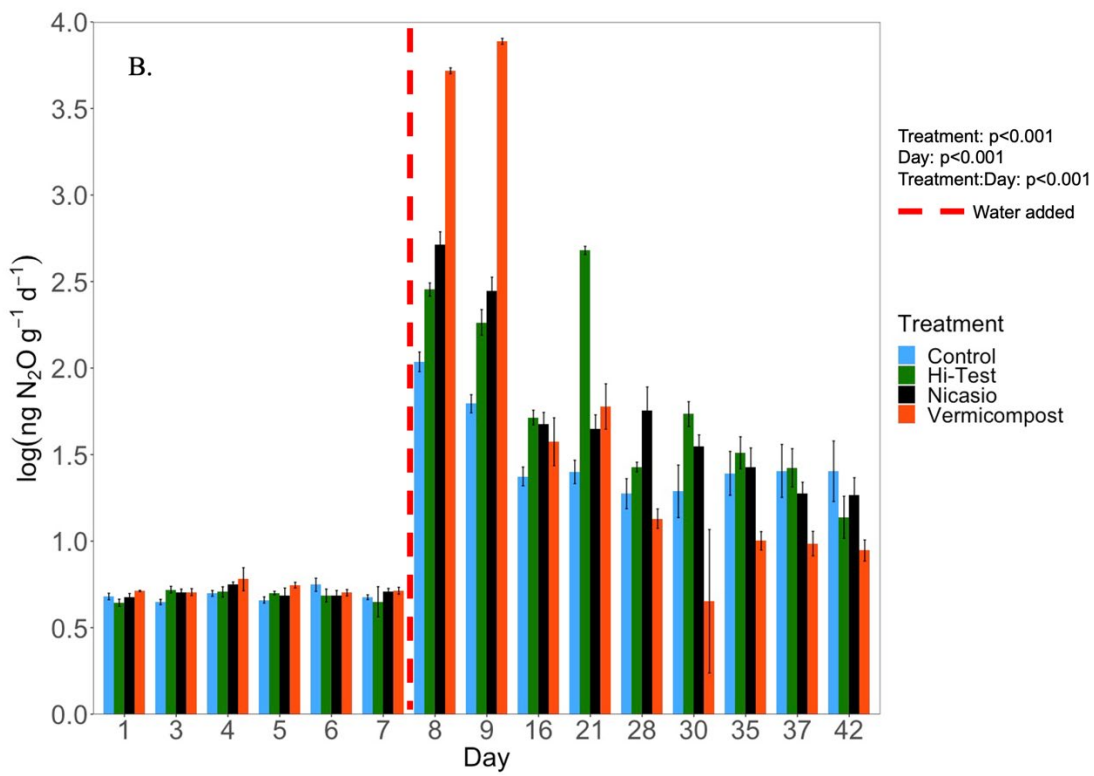
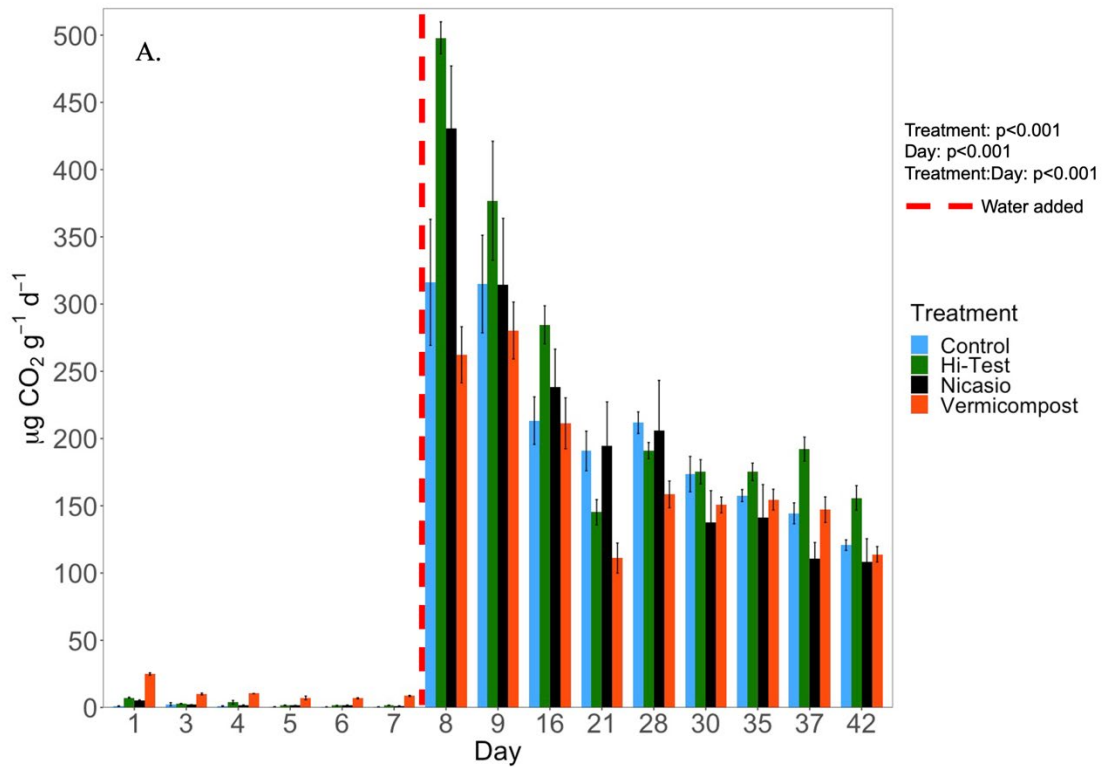
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Appendix

Supplemental Figures



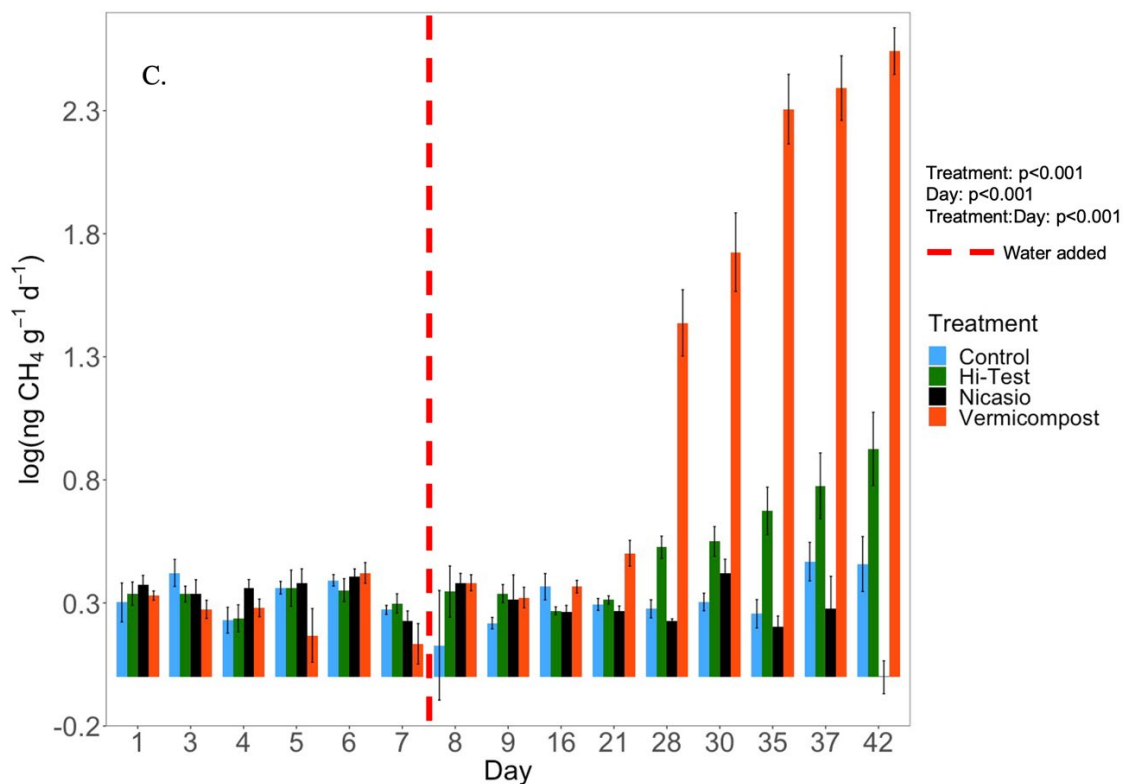
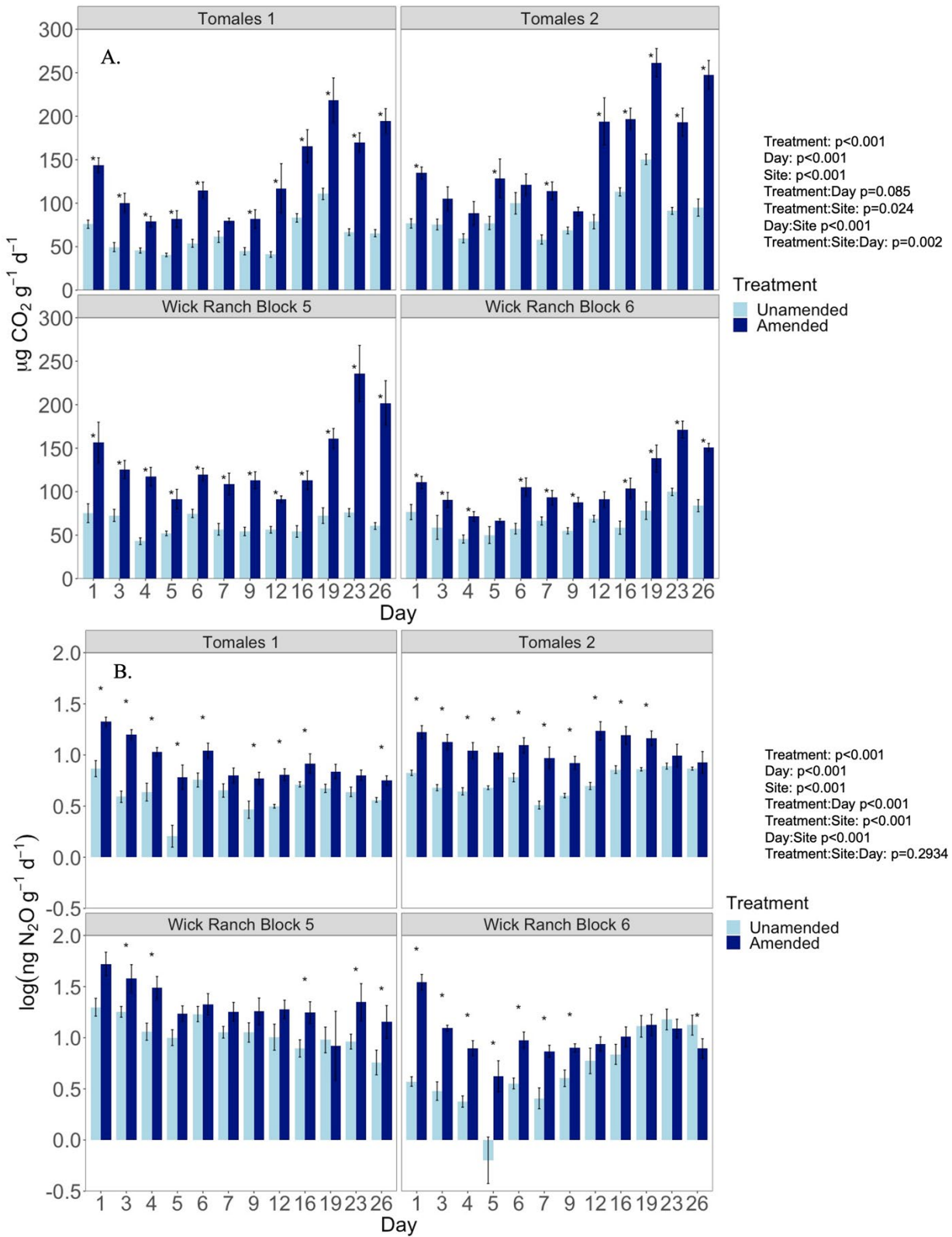


Figure A1: CO_2 (A), N_2O (B), and CH_4 (C) emissions in soils amended with various compost types during a six-week incubation period. N_2O and CH_4 was \log_{10} -transformed. The red dotted line represents when water was added in experiment. Error bars are standard errors.



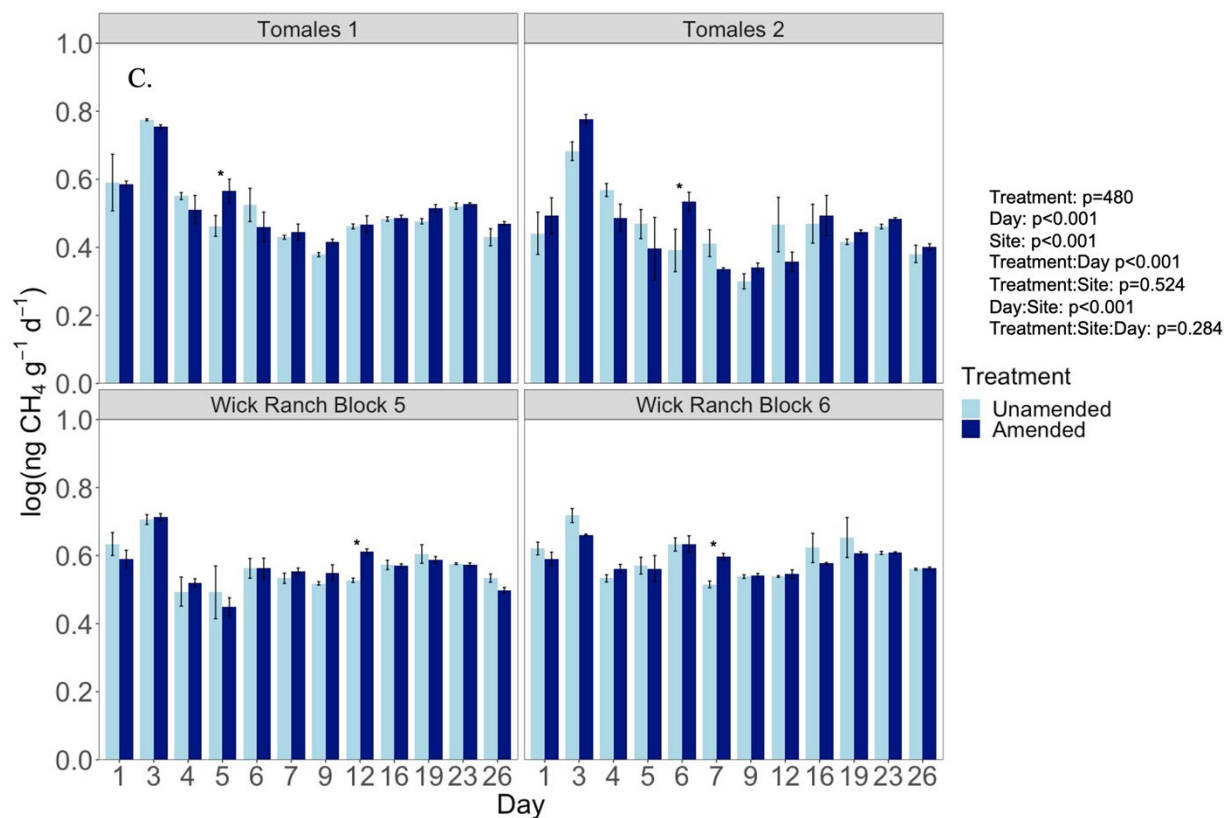


Figure A2: CO₂ (A), N₂O (B), and CH₄ (C) emissions from unamended and composted soils from four locations in a four-week incubation experiment. N₂O and CH₄ data was log₁₀-transformed. Error bars represent standard errors.

Figure Narrative Descriptions

Figure 1 description: Mean N₂O (top), CO₂ (middle), and CH₄ (bottom) emissions in soils amended with different composts and an unamended control. The x-axis is treatment: control, Hi-Test, Nicasio, and Vermicompost. The y-axis shows ng N₂O g⁻¹ d⁻¹ (top), µg CO₂ g⁻¹ d⁻¹ (middle), ng CH₄ CO₂-C g⁻¹ d⁻¹ (bottom).

- Data highlights:
 - Vermicompost showed significant treatment differences for CH₄.

Figure 2 description: Total soil C (A left) and N (B right) at the end of the six-week incubation. Treatments included: an unamended control, Hi-Test compost, Nicasio compost, and Vermicompost. Hi-Test is shown to be significantly different for total soil C. The y-axis shows C (g kg⁻¹) and N (g kg⁻¹) and the x-axis shows treatments.

- Data highlights:
 - The Hi-Test treatment had significantly more C than the other treatments.

Figure 3 description: Weekly pH measurements during the six-week duration of the incubation experiment. The x-axis shows week and the y-axis shows pH. Treatments are an unamended control, Hi-Test compost, Nicasio compost, and Vermicompost. A red dotted line is shown at week 1 showing that water was added at the end of that week.

- Data highlights:
 - All treatments followed the same pattern with increasing pH for the first three to four weeks.
 - Vermicompost had the highest pH, followed by Hi-Test compost.

Figure 4 description: Mean (+/- standard errors) greenhouse fluxes with and without compost amendments for four difference rangeland soils. N₂O flux as ng N₂O g⁻¹ d⁻¹ (top) CO₂ flux as µg CO₂ g⁻¹ d⁻¹ (middle), and Ch₄ flux as ng CH₄-C CH₄ g⁻¹ d⁻¹ (bottom).

- Data highlights:
 - The compost treated soils had significantly higher mean N₂O and CO₂ emissions at all sites.

Figure 5 description: Total soil C (A) and N (B) is shown in a four-panel figure for each element. The data shows soil C and N following a four-week experiment where soils from 4 sites were amended with one compost and incubated for four weeks. Error bars are standard errors.

- Data highlights:
 - There were no statistically significant differences among treatments.

Figure 6 description: Soil pH (mean +/- standard errors) is shown in a four-panel figure with and without compost addition to four different rangeland soils. The x-axis shows week, and the y-axis shows pH.

- Data highlights:
 - The compost treated soils had significantly higher pH.

Figure 7 description: Figure shows N₂O emissions in relation to N application rate from different composts. The composts shown are: food waste compost, composted manure, green waste compost, green waste compost+sludge, green waste compost+biochar, and green waste compost+manure. X-axis is N Application Rate (kg/ha) and the y-axis is g N₂O-N ha⁻¹ day⁻¹.

- Data highlights:
 - There were no significant linear relationships.

Figure 8 description: N₂O emissions versus C:N ratio of various composts in published studies. The composts shown are: food waste compost, composted manure, green waste compost, green waste compost+sludge, green waste compost+biochar, and green waste compost+manure. X-axis is C:N ratio of compost types and the y-axis is g N₂O-N ha⁻¹ day⁻¹.

- Data highlights:
 - There was a weak significant linear relationship.

Figure 9 description: Compost type in relation to N₂O emissions across studies. Values on top of bars indicate number of studies. Error bars are standard errors. The composts shown are: food waste compost, composted manure, green waste compost, green waste compost+sludge, green waste compost+biochar, and green waste compost+manure. X-axis is compost type and the y-axis is g N₂O-N ha⁻¹ day⁻¹.

- Data highlights:
 - There were no significant relationships.

All figures except Figure 13 are two panel scatter plots comparing simulated (vertical axis) versus measured (horizontal axis) values of various soil and flux variables. Panel A shows calibration results and panel B shows validation results. In every panel, “Measured (g m⁻²)” is on the x-axis and “Simulated (g m⁻²)” on the y-axis, with a diagonal dashed line marking perfect 1:1 agreement. Simulations’ MRE and RRMSE, RSD, and IoA are shown.

Figure 10 description: Soil Organic Carbon (SOC)

- Panel A (SOC A):

- Axes: 3,000–11,000 g m⁻²
- Metrics: MRE = 0.11; RRMSE = 0.18; RSD = 0.22; IoA = 0.79
- Treatments: Control, GreenWaste11, GreenWaste16, GreenWaste16×2
- Counties: Alameda, Marin, Mendocino, San Mateo–Pescadero, Santa Barbara, Solano, Sonoma, Yolo, Yuba
- Data: Cluster at 4,000–7,000 g m⁻²; one control site at ~10,000 measured vs. ~11,000 simulated
- Panel B (SOC B):
 - Axes: 4,000–11,000 g m⁻²
 - Metrics: MRE = 0.04; RRMSE = 0.25; RSD = 0.17; IoA = 0.50
 - Treatments: FoodWaste16, FoodWaste16×2, GreenWaste16, GreenWaste16×3, GreenWaste18
 - Counties: Alameda, Mendocino, San Mateo–Pescadero, Santa Barbara, Solano, Sonoma, Yolo, Yuba
 - Data: Simulated 5,500–7,700 vs. measured 5,500–8,000

Figure 11 description: Soil Organic Nitrogen (SON)

- Panel A (SON A):
 - Axes: 300–1,000 g m⁻²
 - Metrics: MRE = –0.06; RRMSE = 0.20; RSD = 0.26; IoA = 0.75
 - Treatments: Control, GreenWaste11, GreenWaste16, GreenWaste16×2
 - Counties: Alameda, Marin, Mendocino, San Mateo–Pescadero, Santa Barbara, Solano, Sonoma, Yolo, Yuba
 - Data: Measured ~350–700 g m⁻², simulated ~400–800 g m⁻²; most points lie just above the 1:1 line
- Panel B (SON B):
 - Axes: ~300–850 g m⁻²
 - Metrics: MRE = –0.16; RRMSE = 0.24; RSD = 0.15; IoA = 0.66
 - Treatments: FoodWaste16, FoodWaste16×2, GreenWaste16, GreenWaste16×2, GreenWaste18
 - Counties: Alameda, Mendocino, San Mateo–Pescadero, Santa Barbara, Solano, Sonoma, Yolo, Yuba
 - Data: Clustered between measured 400–700 and simulated 400–800 g m⁻², primarily below the 1:1 line

Figure 12 description: Biomass Carbon (Biomass C)

- Panel A (Biomass C A):
 - Axes: 0–600 g m⁻²
 - Metrics: MRE = 0.21; RRMSE = 0.52; RSD = 0.64; IoA = 0.86

- Treatments: Control, GreenWaste11, GreenWaste16, GreenWaste16×2, GreenWaste16×3
- Counties: Alameda, Marin, Mendocino, San Diego, San Mateo, Santa Barbara, Solano, Sonoma, Yolo, Yuba
- Data: Measured ~20–450; simulated up to ~600
- Panel B (Biomass C B):
 - Axes: 50–280 g m⁻²
 - Metrics: MRE = 0.22; RRMSE = 0.38; RSD = 0.33; IoA = 0.45
 - Treatments: FoodWaste16, FoodWaste16×2, GreenWaste18
 - Counties: Alameda, Mendocino, San Diego, San Mateo–Pescadero, Santa Barbara, Solano, Sonoma, Yuba
 - Data: Measured ~80–250 versus simulated ~110–205

Figure 13 description: Biomass Nitrogen (Biomass N)

- Panel A (Biomass N A):
 - Axes: 1–8 g m⁻²
 - Metrics: MRE = 0.13; RRMSE = 0.28; RSD = 0.40; IoA = 0.82
 - Treatments: Control, GreenWaste11, GreenWaste16, GreenWaste16×2
 - Counties: Marin, Yuba
 - Data: Measured and simulated both span ~2–6 g m⁻²

Figure 14 description: Cumulative N₂O-N Emissions (N₂O_N)

- Panel A (N₂O_N A):
 - Axes: 0–0.09 g m⁻²
 - Metrics: MRE = 0.33; RRMSE = 1.02; RSD = 1.51; IoA = 0.79
 - Treatments: Control, GreenWaste11, GreenWaste16, GreenWaste16×2
 - Counties: Marin, Yuba
 - Data: Most values <0.02 g m⁻², except one site at measured ~0.08/simulated ~0.03
- Panel B (N₂O_N B):
 - Axes: 0–0.06 g m⁻²
 - Metrics: MRE = 0.61; RRMSE = 1.48; RSD = 1.52; IoA = 0.36
 - Treatments: Control, FoodWaste16, FoodWaste16×2, GreenWaste16
 - County: Yuba only
 - Data: All emissions <0.015 g m⁻²

Figure 15 description: Cumulative CO₂-C Emissions (CO₂_C)

- Panel A (CO₂_C A):
 - Axes: 0–900 g m⁻²
 - Metrics: MRE = –0.24; RRMSE = 0.74; RSD = 1.00; IoA = 0.79
 - Treatments: Control, GreenWaste16, GreenWaste16×2
 - County: Yuba only
 - Data: Control (measured 400–900 vs. simulated 150–480); GreenWaste16 sites cluster closer to 1:1
- Panel B (CO₂_C B):
 - Axes: 0–700 g m⁻²
 - Metrics: MRE = –0.17; RRMSE = 0.57; RSD = 0.70; IoA = 0.77
 - Treatments: Control, FoodWaste16, FoodWaste16×2, GreenWaste16, GreenWaste18
 - Counties: Marin, Yuba
 - Data: Simulated 80–450 vs. measured 20–700

Figure 16 description: A two-panel bar chart comparison of measured versus simulated annual changes in soil C and N stocks (with standard-error whiskers showing variability over each study's duration).

- Panel A (ΔSOC per year):
 - Axes: Vertical axis runs from –500 to +1,400 g m⁻² yr⁻¹; horizontal arranges 12 facet panels by County → Study → Treatment
 - Facets (rows, left to right, top to bottom):
 1. Marin – Study 1 – Control
 2. Marin – Study 1 – GreenWaste11
 3. Yuba – Study 1 – Control
 4. Yuba – Study 1 – GreenWaste11
 5. Yuba – Study 2 – FoodWaste16
 6. Yuba – Study 2 – FoodWaste16×2
 7. Yuba – Study 2 – Control
 8. Yuba – Study 2 – GreenWaste16
 9. Yuba – Study 2 – GreenWaste16×2
 10. Yuba – Study 2 – GreenWaste16×3
 11. Yuba – Study 2 – Unburned Control
 - Data highlights:
 - Study 1 (Marin) shows small negative ΔSOC for Control and GreenWaste11 in both measurement and simulation.
 - Study 1 (Yuba) shows a near-zero ΔSOC for Control and slightly small increase under GreenWaste11.
 - Study 2 (Yuba) yields much larger measured ΔSOC for all green-waste and food-waste treatments (up to ~1,400 g m⁻² yr⁻¹), whereas simulations remain small.

- Panel B (Δ SON per year):
 - Axes: Vertical axis from -40 to $+120 \text{ g m}^{-2} \text{ yr}^{-1}$; same facet layout as Panel A.
 - Data highlights:
 - Study 1 (Marin) shows a small negative measured Δ SON under Control and near-zero simulation; GreenWaste11 is near zero in both.
 - Study 1 (Yuba) shows a modest positive measured Δ SON ($\sim 50 \text{ g m}^{-2} \text{ yr}^{-1}$) under Control and GreenWaste11, matched by simulation.
 - Study 2 (Yuba) shows larger measured Δ SON under FoodWaste16 ($\sim 80\text{--}120 \text{ g m}^{-2} \text{ yr}^{-1}$) and FoodWaste16 \times 2 ($\sim 100 \text{ g m}^{-2} \text{ yr}^{-1}$), with simulations near zero; Control and GreenWaste16 treatments have much smaller changes in both measurement and simulation.

Figure A1 description: CO_2 in $\mu\text{g CO}_2 \text{ g}^{-1} \text{ d}^{-1}$ (A), N_2O in $\text{ng N}_2\text{O g}^{-1} \text{ d}^{-1}$ (B), and CH_4 in $\text{ng CH}_4 \text{ g}^{-1} \text{ d}^{-1}$ (C) emissions from soils amended with one of the four compost types during a six-week incubation period. Bars show each day of the incubation. N_2O and CH_4 was \log_{10} -transformed. The red dotted line represents when water was added in experiment. Error bars are standard errors.

Figure A2 description: CO_2 in $\mu\text{g CO}_2 \text{ g}^{-1} \text{ d}^{-1}$ (A), N_2O in $\text{ng N}_2\text{O g}^{-1} \text{ d}^{-1}$ (B), and CH_4 in $\text{ng CH}_4 \text{ g}^{-1} \text{ d}^{-1}$ (C) emissions from unamended and compost-amended soils from four locations in a four-week incubation experiment. Bars show each day of the incubation. N_2O and CH_4 data was \log_{10} -transformed. Error bars represent standard errors.