Impacts of organic amendments and fertilizers on soil nitrogen cycling in agricultural systems

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Background:

Feeding humanity is dependent on nitrogen (N) inputs into agricultural systems. Yet, we have altered its biogeochemical cycling to the point where it is now considered one of the primary global environmental concerns in the 21st Century (UNEP, 2019). Synthetic N began to be manufactured via the Haber-Bosch process only 100 years ago and now contributes an estimated 120 Tg N yr $^{-1}$ to the global N budget (Erisman et al., 2008; Galloway et al., 2013). Reactive N pollution is now a direct threat to the wellbeing of both human and ecological systems through toxic discharges into marine environments (Camargo and Alonso, 2006), fresh surface and groundwater drinking sources (Carpenter et al., 1998; Sebilo et al., 2013), as well as through ammonia volatilization, NOx production and N_2O emissions into the atmosphere (Tian et al., 2016). Reducing these negative outcomes require us to improve our scientific understanding of N use in cropping systems and communicate practical solutions to stakeholders who have direct influence over N loss, such as farmers.

Sustainably managing N for agricultural production is fundamental to rebalance the global N cycle as demand for food will exacerbate the N problem with increased needs for fertilizer inputs, particularly in developing countries (Alexandratos and Bruinsma, 2012). A key to mitigating the associated public health and environmental repercussions is improving N use efficiency (NUE). It is estimated that NUE in the developed world must increase to 75%, and to 60-70% in much of the rest of the world, in order to meet future sustainability targets (Zhang et al., 2015). The optimization of NUE is contingent upon the alignment between peak N uptake in the crop growth cycle and soil N availability – termed "synchrony" (Cassman et al., 2002).

Paralleling this call to improve NUE is the recognition of the import role increasing soil carbon (C) has in mitigating the impacts of climate change (Minasny et al., 2017). One proposed management technique to increase soil C is the application of organic amendments (Paustian et al., 2016). Although, the impact of increasing soil C, as well as the use of exogenously applied organic materials on NUE is currently unclear (Oelofse et al., 2015; Chen et al., 2018). Whether these materials are used in conventional or organic production, this lack of clarity has the potential to foster misuse resulting in additional nutrient losses or applications that negatively impact NUE (Pan et al., 2018). Understanding how organic materials impact the soil N cycle is paramount to achieve the goal of simultaneously reducing exports of reactive N while increasing soil C.

Research Goals:

- Improve the understanding of how environmental and soil edaphic characteristics influence N release dynamics of organic fertilizers and amendments; this understanding will contribute to better predict plant available N.

- Evaluate how composts with different C qualities impact soil C and N biogeochemical processes when applied to soil with different textures.

- Investigate the effect of compost on fertilizer N availability, at field scale, to better understand nutrient management strategies that increase NUE and reduce system-wide fertilizer N loss while increasing soil C co-benefits.

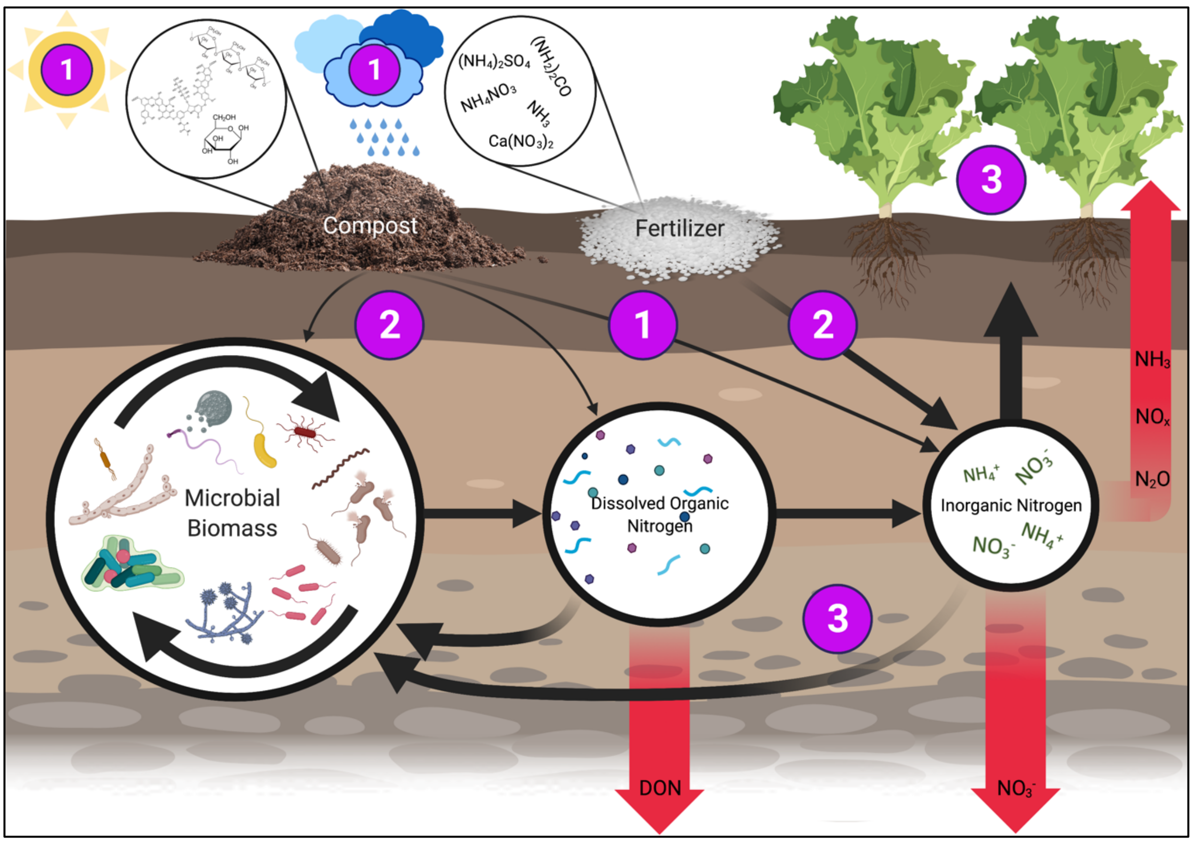

Figure 1. Conceptual diagram depicting the areas of focus covered by the proposed research (purple circles correspond to aims). 1) My first aim involves investigating the impact of environmental factors on net N release from organic amendments. 2) The second seeks to quantify impacts of amendment application on gross N transformations as they relate to soil type and amendment characteristics. 3) And the third will look at how fertilizer N is influenced by organic amendment additions at field scale, inclusive of crop growth.

Research Plan

Aim I: *Model temperature and moisture impacts on N release from organic fertilizers and amendments using literature data.*

Rationale:

In order to optimize the use of organic fertilizers and amendments, factors controlling plant N availability from these materials must be identified. The use of first-order exponential models to estimate potentially available N from organic materials has long been employed, examples include a single pool model (Hadas and Portnoy, 1994) representing one mineralizable pool or a two pool model representing a fast release pool followed by a second slower pool (Gordillo and Cabrera, 1997). Studies that have compared multiple models (Cordovil et al., 2005; Gil et al., 2011) have generally favored single pool representation. Recent studies evaluating a wide variety of amendments have shown that amendment type significantly impacts predicted potentially available N (N_0) (Lazicki et al., 2019; Cassity-Duffey et al., 2020). Although these studies are useful for comparing amendments based on the C and N composition, challenges remain in understanding how other factors, beyond amendment type, such as environmental conditions or soil properties impact N availability and the rate of N release from these pools.

Due to the cumbersome nature of long-term incubation experiments it is difficult to evaluate multiple factors at once. Ideally, data could be extracted directly from multiple studies and compared. Yet, this is not advised due to challenges associated with extracting parameter values directly from the literature such as the different individual incubation conditions, time periods and amendment types (Dou et al., 1996). In addition, comparing non-linear model parameters that are fit using optimization algorithms is fraught with error due to the relationship between local-minima searches and parameter initiation values (Dendooven et al., 1997). Recent work by Sradnick and Feller (2020) achieved comparison across incubation studies by fitting the single pool model to data points extracted from the literature. Their results reaffirm previous findings that the ratio of C to organic N is an adequate predictor of N_0. Yet, they found high variability in the mineralization rate constant *k* and were not able to identify appropriate predictors, yet this has previously shown to be influenced by temperature (De Neve et al., 1996). Here I propose to fit two selected N mineralization models to data extracted from the literature. I will then use the generated parameter values to establish temperature and moisture response functions. The literature data is expected to be biased towards optimal conditions for nitrification which will limit the ability to evaluate N mineralization responses under all desired temperature and moisture ranges. To overcome this obstacle, I propose to use a Bayesian hierarchical modeling framework in order to establish probability estimates of parameter values for *k*, using prior literature information, under temperature and moisture conditions not adequately represented in the literature.

Question:

Q1.1 Can the influence of environmental factors such as soil moisture and temperature on net N mineralization from organic fertilizers and amendments be predicted?

Objectives:

1.1 Use literature data to determine parameter values and associated uncertainty for selected non-linear models predicting N release characteristics of organic amendments and fertilizers.

1.2 Quantify the uncertainty of model parameters associated with changes in environmental conditions and estimate the effects of these changes under selected scenarios.

Hypothesis 1: N release rates (*k*) will be impacted differently by environmental conditions, with high N materials displaying less variability to changes in temperature and moisture compared to low N materials.

Approach: A literature search will be conducted using terms: "organic amendments," "organic fertilizers," "compost," "manure," and "incubation." Criteria for extraction of data from individual studies will include only incubations measuring mineralized inorganic N conducted under aerobic conditions without the presence of plants, with each reporting measurements of mineral N (NH_4^+ and NO_3^-, or combined), include organic fertilizers or amendments that are under C:N ratio 16 (to avoid negative net N mineralization values), and total organic N of the amendments. A strict requirement will be that the study provide a reported value or allow for the calculation of, using an unamended control, net N mineralization from the applied organic N pool of the individual amendments. Modeling will take place in two stages; first model parameters will be derived from extracted data in order to calculate temperature and moisture response functions. This then will be followed by construction of the hierarchical model in order to estimate the variance in temperature and moisture response functions at the study level. This information will then be used to inform estimates of the responses under conditions lacking data. According to Bayesian analysis, both prior and likelihood functions must be determined in accordance with Bayes theorem, p(B|A) = p(A|B)p(B)/p(A). Below are the chosen non-linear N mineralization models, models for the temperature and moisture functions, as well as the statistical models for Bayesian inference.

N Mineralization Models

Single pool (m1): $$N_{min} = N_0(1 - e^{-k_0 t})$$ (Stanford and Smith, 1972)

Double pool (m2): $$N_{min} = N_1(1 - e^{-k_1 t}) + N_2(1 - e^{-k_2 t})$$ (Hadas et al., 1983)

Single and double pool nonlinear exponential regression models will be fit to all amendment type categories. The single compartment model represents one potentially mineralizable pool N_0 (as % of added organic N), fit to measured cumulative mineralized N from the amendment (N_{min}) over time period *t,* released at rate *k* ($week^{-1}$). Different from the single compartment model, the double pool representation describes two discrete pools, a faster turnover pool (N_1) and a slower turnover pool (N_2), with individual respective turnover rates (k_1, k_2).

Temperature: $$f_T = Q_{10}^{(T-T_{ref})/10}$$ (Rodrigo et al., 1997)

Q_{10} Calculations $$Q_{10(k_0)} = \left(\frac{k_{t2}}{k_{t1}}\right)^{\frac{10}{T2-T1}}$$ (Zang et al., 2020)

$$Q_{10(k_1)} = \left(\frac{k_{1t2}}{k_{1t1}}\right)^{\frac{10}{T2-T1}}$$

$$Q_{10(k_2)} = \left(\frac{k_{2t2}}{k_{2t1}}\right)^{\frac{10}{T2-T1}}$$

Here f_T represents the temperature response function, with T representing the variable temperature and T_{ref} the temperature constant which will be set to 35°C. The Q_{10} value represents an exponential function and has no biological interpretation. After calculation of Q_{10} values from extracted data, using either single or double pool model parameters, respective f_T will be determined to inform the model below. To calculate Q_{10} values for either the single or double pool models, each fit parameter for *k* will be used at two respective temperatures T.

Moisture: $$f_w = k_{opt}^{-\xi(1-\frac{W}{W_{opt}})^2}$$ (De Neve and Hofman, 2002)

Here f_w represents the soil moisture response function, with k_{opt} representing the mineralization rate at W_{opt}, the optimal gravimetric water content (GWC). W is the actual GWC and ξ is a parameter depicting the moisture dependance of N mineralization. Under the two-pool model, k_{opt} will be either $k_{opt(1)}$ or $k_{opt(2)}$.

Bayesian Inference	*Model 1 – one pool*	*Model 2 – two pool*
Data model	$y_{ij}^{obs} = N_0(1 - e^{-k_0*[f_T*f_w]t})$	$y_{ij}^{obs} = N_1(1 - e^{-k_1*[f_T*f_w]t}) + N_2(1 - e^{-k_2*[f_T*f_w]t})$
	$\theta_{m1} = (N_0, k_0)$	$\theta_{m2} = (N_1, N_2, k_1, k_2,)$

The data model shown above represents the observed value of net N mineralization (y_{ij}^{obs}) of observation *i* within study *j*, as a non-linear function, shown as a vector of parameters from model *x* (ie.1, 2) (θ_x), depicting potentially mineralizable N ($N_{0,1,2}$), the temperature and moisture adjusted turnover rate ($k_{0,1,2}$), and incubation time (*t*). Values of the temperature (f_T) and moisture (f_w) response functions are treated as known values with a deterministic relationship to *k*.

Likelihood	$y_{ij}^{obs} \sim lognormal(\theta_{m1}, \sigma_j^2)$	$y_{ij}^{obs} \sim lognormal(\theta_{m2}, \sigma_j^2)$

The above likelihood function describes the process model fit to observed values (y_{ij}^{obs}), lognormally distributed around the mean prediction of the function θ_x of observation *i*, indexed to study *j*, with observation-level parameter variance (σ_j^2).

Priors	$k \sim lognormal(\mu, \sigma^2)$	$k_1 \sim lognormal(\mu, \sigma^2)$
	$N_0 \sim lognormal(\mu, \sigma^2)$	$k_2 \sim lognormal(\mu, \sigma^2)$

$$f_T \sim lognormal(\upsilon_{f_T}, \tau_1^2) \qquad N_1 \sim lognormal(\mu, \sigma^2)$$
$$f_w \sim lognormal(\upsilon_{f_w}, \tau_2^2) \qquad N_2 \sim lognormal(\mu, \sigma^2)$$
$$\tau_1^2 \sim inverse - gamma(\alpha, \beta) \qquad f_{T1} \sim lognormal(\upsilon_{f_T1}, \tau_1^2)$$
$$\tau_2^2 \sim inverse - gamma(\alpha, \beta) \qquad f_{w1} \sim lognormal(\upsilon_{f_{w1}}, \tau_2^2)$$
$$\upsilon_{f_T} \sim normal(\mu, \sigma^2) \qquad f_{T2} \sim lognormal(\upsilon_{f_T2}, \tau_3^2)$$
$$\upsilon_{f_w} \sim normal(\mu, \sigma^2) \qquad f_{w2} \sim lognormal(\upsilon_{f_{w2}}, \tau_4^2)$$
$$\upsilon_{f_{T1}} \sim normal(\mu, \sigma^2)$$
$$\upsilon_{f_{w1}} \sim normal(\mu, \sigma^2)$$
$$\upsilon_{f_{w2}} \sim normal(\mu, \sigma^2)$$
$$\upsilon_{f_{T2}} \sim normal(\mu, \sigma^2)$$
$$\tau_1^2 \sim inverse - gamma(\alpha, \beta)$$
$$\tau_2^2 \sim inverse - gamma(\alpha, \beta)$$
$$\tau_3^2 \sim inverse - gamma(\alpha, \beta)$$
$$\tau_4^2 \sim inverse - gamma(\alpha, \beta)$$

Prior values are lognormally distributed, as model parameters θ_x must be nonzero. For the study level variance related to parameters f_T and f_w (τ_x^2) an inverse-gamma distribution was chosen as the appropriate conjugate prior for a lognormal distribution with a known mean. Importantly, when f_T and f_w values are observed from the literature data, the above associated distributions are considered likelihood functions but when these values are treated as missing (ie. temperature and moistures not in the literature), they will be considered priors.

The generalized posterior and joint probability distributions can then be written as:

$$p(\theta_{mx}, \sigma_j^2, \tau_x^2, \upsilon_{f_x} | y)$$
$$\propto \prod_{j=1}^{j} \prod_{i=1}^{n} p(\, y_{ij} | \theta_{mx}, \sigma_j^2) \times$$
$$p(k_x | \mu, \sigma^2)\, p(N_0 | \mu, \sigma^2) p(f_x | \upsilon_{f_x}, \tau_x^2) p(\upsilon_{f_x} | \mu, \sigma^2) p(\tau_x^2 | \alpha, \beta)$$

All models will be programed using the Stan probabilistic programing language (Stan Development Team, 2019) within the statistical computing software R (R Core Team, 2020). Sampling of the parameter space will be carried out using the MCMC algorithm. Which, in short, will sample via making multiple random draws from the marginal posteriors of the parameters of interest. Convergence will be monitored and verified using the Gelman-Rubin diagnostic $\hat{r}$ (Gelman et al., 2014). After which, parameter means, variance and credibility intervals will be determined. In order to test whether temperature and moisture impact the k constants differently the credible intervals will be compared under different environmental exposures. If the intervals overlap the null hypothesis, f_T and f_W had no effect, will be accepted.

Preliminary results:

Work associated with this project is currently on-going with preliminary results from data extracted from 28 studies out of 56 total studies currently selected for inclusion. These results show that low C:N ratio organic fertilizers (Supp. *figure 1b*) demonstrate a lower variability in parameter values and show a linear trend with increasing N content whereas compost (Supp. *figure 1a*), with a higher C:N ratio, does not show this trend with much higher variability as shown by the wide estimated confidence intervals. Parameter uncertainty was variable across observations when comparing C:N ratios. Potentially mineralizable N (N_0) differed significantly between amendment types ($p<0.05$), yet not the k values representing turnover rates ($p=0.12$), indicating an independence from N pool sizes and the contribution of other factors over N release rates other than total N content of the material (Figure 2). Initially, I expect that the N mineralization models will fit amendment types differently, with the two-pool showing better fit for amendments of complex composition. This will likely be confirmed using K-fold cross validation that will compare the model to out-of-sample data from additional literature data not included in the training data set. Additionally, the impact of temperature is expected to be higher for recalcitrant organic N pools, depicted by the two-pool model. This will be shown by overlapping credibility intervals for k_0 and k_1 under exposure to different environmental conditions but not for k_2, for both observed and estimates based on imputed data.

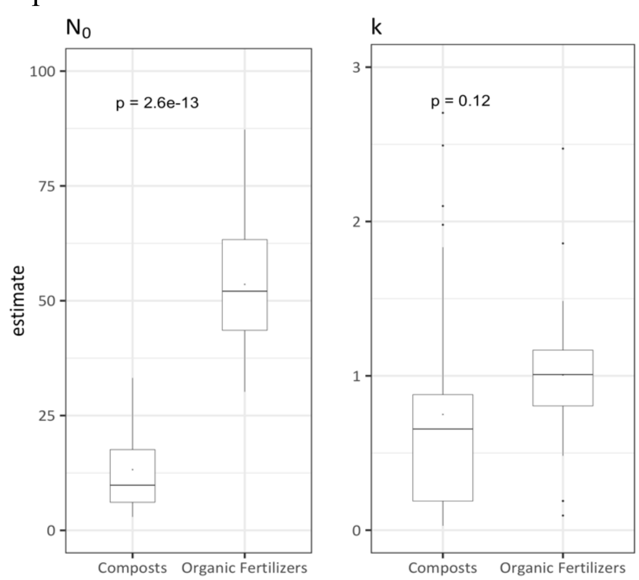

Figure 2: Box plots representing mean values for data collected from literature studies. Mean is depicted by the point and median the line. Parameter values shown on the y-axis and the amendment type (compost or organic fertilizer) across the bottom. N_0 is potentially mineralizable N and k in the calculated rate constant.

Aim II: *Determine the importance of compost biochemical fractions and soil edaphic factors on N transformation processes.*

Rationale:

Understanding the impact of organic amendments on N cycling processes is critical to balancing both microbial and plant demand for N in order to meet long-term nutrient management and environmental protection objectives (Masunga et al., 2016). Directly quantifying the effects of organic amendments on N turnover will enhance application recommendations that aim to improve crop N use efficiency (NUE) and reduce N losses from agroecosystems as leached NO_3^- or gaseous N_2O. Although routinely used to predict N availability from organic amendments, C:N ratio has shown to be a weak indicator – specifically for complex C substrates such as compost (Bonanomi et al., 2019). Previous work on biochemical quality of added organic materials, including composts, has shown that labile C forms, such as sugars and starches, serve as important controls over N mineralization from amendments (Valenzuela-Solano and Crohn, 2006) as well as N containing C compounds (Xu et al., 2020), cellulose, ash and lignin (Flavel and Murphy, 2006). Currently, there is limited research connecting N transformation as impacted by biochemical composition to varying soil edaphic and environmental conditions for composts and other organic N containing amendments of similar C:N ratios. The proposed research will contribute to the understanding of compost N dynamics in agricultural systems as well as provide empirical data to evaluate ecosystem scale biogeochemical models, such as DAYCENT, which uses both amendment C:N and lignin:N ratio to determine crop N availability and system wide losses.

Questions:

Q2.1 Which factor is most dominant in controlling gross N transformations: soil edaphic characteristics or amendment C qualities?

Q2.2 Can this dominance be explained by shifts in microbial metabolism as a function of compost carbon availability?

Objectives:

2.1 Quantify the effects of compost amendments with similar C:N ratios but varying C and N qualities on multiple gross N transformation rates across different soils with contrasting textures.

2.2 Determine the relationships between compost C quality, soil microbial biomass size and metabolism, and gross N transformation rates in soils with varying edaphic characteristics.

Hypothesis 2: The compost with the highest ratio of acid-insoluble fraction to water extractable organic C (WEOC) ratio will have the slowest immobilization rate and highest net nitrification rate.

- This effect will not be consistent across selected soils due to the differences in organic matter content, texture and associated microbial characteristics.

General approach: Soil sampling will take place throughout the Salinas Valley from agricultural sites with vegetable cropping histories, a total of three contrasting soil series – Cropley (Fine, smectitic, thermic Aridic Haploxererts), Salinas (Fine-loamy, mixed, superactive, thermic Pachic Haploxerolls), Metz (Sandy, mixed, thermic Typic Xerofluvents). These series make up a large portion of the total soil types within the valley floor under intensive annual crop cultivation. Using a paired ^{15}N isotope tracer aerobic laboratory incubation experiment, different gross N cycling processes rates will be determined by fitting models to direct enrichment measurements from inorganic and organic N pools. Briefly, treatments will be arranged in a replicated full-factorial design consisting of an un-amended control with three compost types applied. Soils will be sieved to 4 mm and analyzed for texture using the pipet method (Gee and Bauder, 1986). Three contrasting composts will be sampled from facilities within the central coast region. Materials will be targeted to have similar C:N ratios but varying cellulose, hemi-cellulose, and lignin-like, acid insoluble fractions as measured by the Van Soest fiber analysis procedure (Soest and Wine, 1967). Additionally, WEOC and N will be measured using both room temperature and 80°C water according to Curtin et al. (2006). Each experimental unit will receive either $^{15}NH_4NO_3$ or $NH_4{}^{15}NO_3$ at a target of 10% atom excess. Samples will be divided into two sets, one for destructive sampling and the other for gas analysis. Measurements of NH_4^+ and NO_3^- will be taken via destructive sampling at time points 0, 0.5, 24, 48, 120, 216, 336 hours. Gas sampling will take place at these same time points from a parallel set of jars. Microbial biomass C:N will be measured at time points 0, 24, 120, 336 hours using the 24-hour chloroform-fumigation technique. Gross N transformation rates will be calculated using a model fitting procedure which simultaneously optimizes for multiple kinetic parameters using the Markov chain Monte Carlo algorithm or MCMC (Müller et al., 2007). Pearson correlations will be calculated to determine the covariance between amendment/soil properties to N process rates. Differences in gross immobilization and net nitrification rates as influenced by amendment acid-insoluble:WEOC ratio and soil type will be evaluated using two-way ANOVA.

Expected results:

A recent meta-analysis, that included compost, has shown that C:N ratio was not an appropriate predictor of gross N immobilization but C compositional markup was consequential (Cao et al., 2021). In the proposed experiment, results are expected to concur with these finding by showing that composts with the highest percentage of labile C fractions will lead faster N immobilization, resulting in lower net nitrification due to a reduction in available N for nitrification. Soil type is likely to exert a dominant effect on net nitrification rates, with higher rates corresponding to increased clay content, in line with previous findings from our lab (Zhu-Barker et al., 2015), yet this effect is expected to be tempered by C availability. It is to be anticipated that labile C in compost will correlate negatively with the microbial metabolic quotient ($q$$CO_2$), a proxy for microbial nutrient use efficiency, indicating a reduction in C limitation. Yet, this experiment will show soil texture and compost C quality has an interactive effect of N transformation rates based on the fact that soils with varying textures have different soil organic matter levels.

Table 1. Description of modeled gross N process rates

#	**Name**
1	Autotrophic nitrification
2	Dissimilatory nitrate reduction to ammonium
3	Immobilization of nitrate into recalcitrant organic N pool
4	Oxidation of recalcitrant organic N
5	Immobilization of ammonium into recalcitrant N pool
6	Mineralization of recalcitrant organic N
7	Mineralization of labile N
8	Immobilization of ammonium into labile N pool
9	Ammonium fixation to mineral complex
10	Release of fixed ammonium

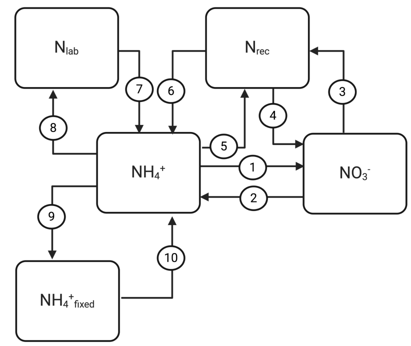

Figure 3: ^{15}N tracing model developed by Müller et al. (2007) for calculating gross N process rates. Five N pools include inorganic ammonium (NH_4^+) and nitrate (NO_3^-), recalcitrant organic N (N_{rec}) and labile organic N (N_{lab}), and fixed ammonium (NH_4^+fixed).

Aim III*: Evaluate the impacts of compost application on fertilizer N use efficiency and retention within vegetable cropping systems*.

Rationale:

Sustainably intensifying high-input cropping systems, such as vegetables, requires improving N fertilizer use efficiency (FUE). One method for achieving this is through increasing retention of fertilizer N within persistent soil N pools, for example soil organic matter, microbial biomass and/or crop roots (Yan et al., 2014). Recent work synthesizing the fate of N fertilizer in cereal crops has shown that nearly 1/3 of the applied fertilizer N can be retained in the soil N pool after a single season (Yan et al., 2020). Here I propose to evaluate how compost, applied with fertilizer N, impacts the crop uptake and loss of the fertilizer from the system. As carbon-rich organic amendments have repeatedly shown to be beneficial to soil health while boosting crop performance (Diacono and Montemurro, 2010; Chen et al., 2018). Applying compost has the potential to both increase long-term FUE while improving soil health. Yet initially compost applications can lead to a reduction in FUE (Choi et al., 2001) making understanding of impacts on the fate of fertilizer N critical to optimizing recommendations for applications.

^{15}N tracer field trials have long been used to follow the fate and distribution of fertilizer N throughout the plant-soil system, but have recently been questioned for their continued scientific usefulness (Smith and Chalk, 2018). One area of opportunity for investigation includes connecting FUE, alternative fertilizer management strategies and N retention. Organic N pools have shown to retain fertilizer N for multiple crop systems, making N potentially available long after application (Shen et al., 1989). The only known long-term (>10 yrs) ^{15}N field trial has shown that approximately 10% of the original fertilizer N was found 23 years after being initially applied (Sebilo et al., 2013). This highlights the importance of understanding how different nutrient management strategies can alter the contribution that inorganic N fertilizers make to persistent soil N pools.

Research Questions:

Q3.1 Does integration of compost with synthetic N fertilizer increase FUE and is this impacted by fertilizer application rate or timing?

Q3.2 When compost is applied close to the time of fertilizer N application, is more fertilizer N retained in the soil over multiple crop rotations and growing seasons?

Objectives:

3.1 Evaluate how the timing and application rate of synthetic N fertilizer, with or without compost, impacts crop FUE over multiple growing seasons.

3.2 Determine the impact of compost application on fertilizer N retention in the bulk and microbial biomass soil N pools over multiple growing seasons.

Hypothesis 3: After the application of compost, FUE will be decreased in the first season but higher FUE will be found over multiple seasons due to initial immobilization of the inorganic N pool and remineralization of the microbial biomass N pool.

- The increase in overall FUE will be higher if N fertilizer was applied before planting and at a lower rate.

Approach:

The field trial is located along California's central coast between the cities of Salinas and Castroville in partnership with SeaMist Farms, a mid-scale diversified cool-season vegetable operation. The field was previously cropped with Artichoke, Broccoli and Brussel sprouts; and managed using conventional practices. A total of ten treatments were set up as a randomized complete block design with three blocks (replicates) during the Spring of 2019. The initial crop planted was Chile Pepper (*Capsicum Annuum*), with subsequent plantings of Broccoli (*Brassica oleracea*) over the 2019-2020 growing season. The treatments (*see Table 2*) include: two compost rates (0 or 6 ton acre^{-1}) * two synthetic fertilizer (urea) rates (238 or 280 kg N ha^{-1}) * two isotope application times (pre-planting or post-planting). In addition, two treatments include no compost/no N and compost plus no N were set up as two controls. The synthetic fertilizer N was split into two applications, pre-plant and 4 weeks after planting, as two or more applications is common practice for vegetables grown in the region.

Table 2 Field treatment structure, ^{15}N and N application rate application times and addition of compost amendment

#	Treatment	Total kg ^{15}N/ha	Total N (kg/ha)	Time	Compost
1	Com + Urea R1 T1	5.6	280	Pre	Yes
2	Com + Urea R1 T2	22.4	280	Post	Yes
3	Com + Urea R2 T1	4.76	238	Pre	Yes
4	Com + Urea R2 T2	19.04	238	Post	Yes
5	Urea R1 T1	5.6	280	Pre	No
6	Urea R1 T2	22.4	280	Post	No
7	Urea R2 T1	4.76	238	Pre	No
8	Urea R2 T2	19.04	238	Post	No
9	Compost	0	0	NA	Yes
10	Control	0	0	NA	No

Given the need to apply ^{15}N-urea separately if multiple fertilization events are to be investigated, timing of tracer application was considered a unique individual treatment (pre and post planting). In the middle 3 rows of each 5-row treatment block, 2 m^2 microplots were installed for isotope applications. ^{15} N-Urea (99.9 atom%) fertilizer at various rates according to 20% of total applied N applied at pre-planting and 80% total N applied 4 weeks after planting, adjusted to full and reduced N rates. Applications of tracer were applied using a powered garden backpack sprayer with a fixed flow rate. At harvest both crops and soils will be sampled. 80 cm, no-contamination soil cores were taken using a hammer driven probe. Each core was divided into depth increments of 0-20, 20-60, 60-80 cm and analyzed for Total C/N, Microbial C/N, NH_4^+, NO_3^-, DOC and TDN. Isotope analysis was carried out by diffusing K_2SO_4 soil extracts with either MgO (NH_4-N) or a combination of MgO and Devarda's alloy (NH_4 +NO_3 -N) and trapped on an acidified disk following Khan et al. (1998). Calculation of fertilizer immobilization into the microbial biomass will follow the difference method of Burger and Jackson (2003). Crop components - biomass and fruit - were dried, ground and analyzed for Total C:N. Both plant and soil samples will be submitted to the UC Davis Stable Isotope Facility for solid ^{15}N isotope analysis. Multivariate analysis of variance (MANOVA) will be used to test the influence of N application rate, time, and compost addition on percentage of fertilizer uptake by the crop verse microbial biomass.

Preliminary results:

Due to the increase in C availability related to compost addition, more fertilizer N is expected to be immobilized into the microbial biomass pool during the first season of application leading to a decrease in apparent FUE, with the highest FUE seen in treatment not receiving compost. This assimilation into the organic N pool will lead to subsequent fertilizer availability the following growing seasons increasing FUE compared to the treatments without compost. Yield data collected over the first growing season and the beginning of the second season support this, showing higher yields were obtained in the reduced N treatment receiving compost for the Broccoli crop following peppers. This could demonstrate the biological retention of initially applied fertilizer, increasing crop synchrony with N uptake the following season. This effect should be pronounced specifically for the pre-plant N application as early N can easily be lost from the system. Comparison of fertilizer partitioning between the crop biomass and the organic N pools will show the importance of compost application in the first season to the fertilizer assimilation into microbial biomass, while in the second and third seasons compost application will show to be more important in plant fertilizer uptake.

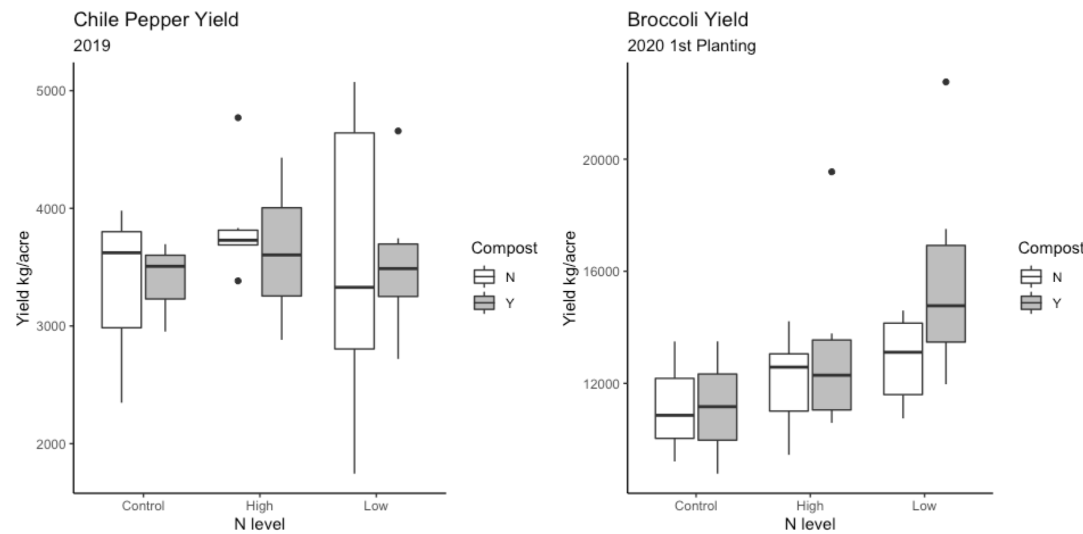

Figure 4: Yields of both pepper and broccoli plantings (Summer 2019, Spring-Summer 2020). Treatments are grouped by N fertilizer application level, control (0 kg N/ha), high rate (280 kg N/ha), and low (238 kg N/ha). White boxes represent treatments with no compost applied. Grey boxes represent treatments with compost applied at a rate of 6 tons/acre.

Conclusions:

The work proposed here has the potential to substantively contribute to the scientific understanding of the soil N cycle within agricultural systems as it is altered by the addition of organic amendments. My intention is to provide meaningful data in order to assist stakeholders involved in making decisions concerning alternative nutrient management strategies involving organic sources of N. Results from the research proposed here aim to support practices that increase NUE while simultaneously improving soil health. Agriculture faces immense challenges in the future as pressures mount to reduce negative environmental outcomes while intensifying production in order to meet increasing demand. Solving this quandary will not be simple yet solutions must be sought that counterbalance humanity's reliance on agricultural inputs with management techniques that advance ecological sustainability.

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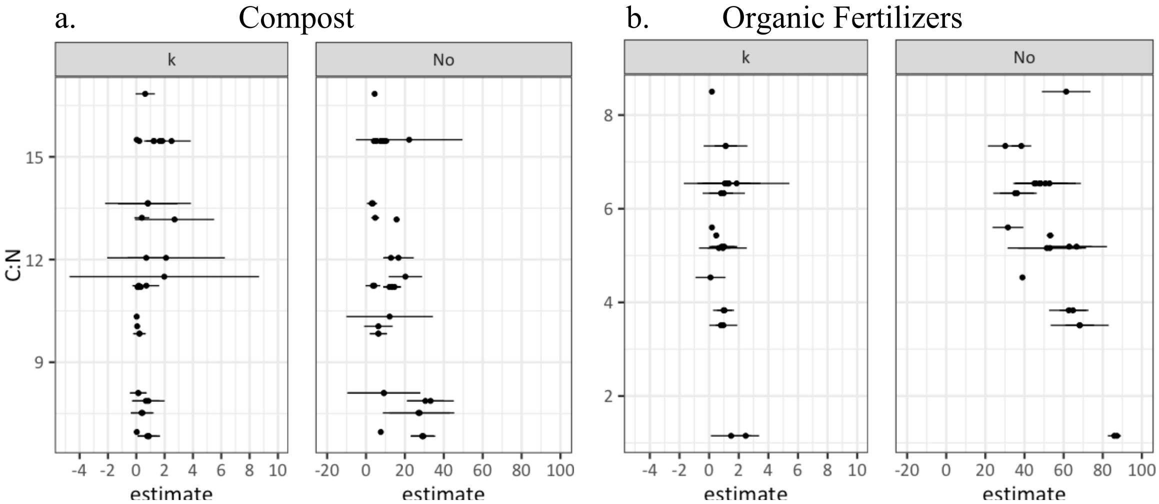
Supplementary Materials



Supplementary figure 1. Single pool exponetial model fits for all studies (16) and observations (46) collected from literature data from compost (a) and organic fertilizers (b). Horizontal axis represents parameter values with the y-axis representing C:N values. Point estimates of parameters are shown in black with confidence intervals (2.5% and 97.5%).