

**Diversity of Nitrogen Cycling Genes at a Midwest Long Term Ecological Research Site
with Different Management Practices**

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Abstract

Nitrogen fertilizer results in the release of nitrous oxide (N₂O), a concern because N₂O is an ozone-depleting substance and a greenhouse gas. Although the reduction of N₂O to nitrogen gas can control emissions, the factors impacting the enzymes involved have not been fully explored. The current study investigated the abundance and diversity of genes involved in nitrogen cycling (primarily denitrification) under four agricultural management practices (no tillage [NT], conventional tillage [CT], reduced input, biologically based). The work involved examining soil shotgun sequencing data for nine genes (*napA*, *narG*, *nirK*, *nirS*, *norB*, *nosZ*, *nirA*, *nirB*, *nifH*). For each gene, relative abundance values, diversity and richness indices and taxonomic classification were determined. Additionally, the genes associated with nitrogen metabolism (defined by the KEGG hierarchy) were examined. The data generated were statistically compared between the four management practices. The relative abundance of four genes (*nifH*, *nirK*, *nirS* and *norB*) were significantly lower in the NT treatment compared to one or more of the other soils. The abundance values of *napA*, *narG*, *nifH*, *nirA* and *nirB* were not significantly different between NT and CT. The relative abundance of *nirS* was significantly higher in the CT treatment compared to the others. Diversity and richness values were higher for four of the nine genes (*napA*, *narG*, *nirA*, *nirB*). Based on *nirS/nirK* ratios, CT represents the highest N₂O consumption potential in four soils. In conclusion, the microbial communities involved in nitrogen metabolism were sensitive to different agricultural practices, which in turn, likely has implications for N₂O emissions.

Key Points

Four genes were less abundant in NT compared to one or more of the others soils (*nifH*, *nirK*, *nirS*, *norB*).

The most abundant sequences for many of the genes classified within the *Proteobacteria*.

Higher diversity and richness indices were observed for four genes (*napA*, *narG*, *nirA*, *nirB*).

Based on *nirS/nirK* ratios, CT represents the highest N₂O consumption potential.

Introduction

An understanding of the terrestrial nitrogen cycle is important both for optimizing agricultural productivity as well as for minimizing environmental impacts, such as water pollution or global warming. Nitrous oxide (N_2O) is a predominant ozone-depleting substance and an important and potent greenhouse gas with a global warming potential over 100 years of ~ 298 and 11.9 times that of CO_2 and CH_4 , respectively (Domeignoz-Horta et al. 2018; Ravishankara et al. 2009). The majority (almost 70%) of the total global N_2O atmospheric loading can be accounted for by terrestrial ecosystems, and at least 45% of this has been attributed to microbial cycling of nitrogen in agricultural systems (Rudy et al. 2008; Syakila and Kroeze 2011). The increasing use of nitrogen fertilizer in agricultural practice has accordingly increased N_2O production (Davidson, 2009). The nitrogen cycle involves two key microbial processes for the emission of N_2O from soils. During nitrification, bacteria produce N_2O during the first step, when ammonia is oxidized to nitrite via hydroxylamine (Prosser and Nicol 2012). Denitrification is another key microbial process for the release of N_2O , involving the respiratory reduction of nitrate (NO_3^-) to nitrite (NO_2^-) and their subsequent reduction to gaseous forms (NO , N_2O , N_2). Although the microbial reduction of N_2O to nitrogen gas is vital for controlling emissions from terrestrial ecosystems, the determinants for a soil to act as a source or a sink remain uncertain (Butterbach-Bahl et al. 2013). Although the importance of nitrification is recognized for nitrous oxide emissions, the current work focused primarily on the enzymes involved in denitrification to favor content depth over breadth.

A number of enzymes are associated with denitrification, including those encoded by nitrate reductases (*napA/narG*), nitrite reductases (*nirK/nirS*); nitric oxide reductase (*norB*) and nitrous oxide reductase (*nosZ*) (Philippot et al. 2007). Many researchers have suggested that the abundance and diversity of such genes can impact N_2O emission rates. For instance, researchers found correlations between the relative abundance of *nosZ* and the potential N_2O production (Domeignoz-Horta et al. 2016). In another study, low N_2O emission rates were explained by soils properties (up to 59%), whereas high rates were explained by the abundance and diversity of the microbial communities (up to 68%) (Domeignoz-Horta et al. 2018). The same study found that the diversity of *nosZ* was important to explain the variation in N_2O emissions (Domeignoz-Horta et al. 2018). Others found that *nirK* gene copy numbers correlated with potential

denitrification, but *nirS* gene copy numbers did not (Attard et al. 2011). Further, researchers have provided evidence of higher *nirS/nirK* ratios and higher N₂O consumption (Jones et al. 2014).

Agricultural practices are also known to influence denitrification trends. Although the impact of no tillage (NT) on N₂O emissions has been widely investigated, the results have been varied. Some studies reported minimal differences of N₂O emissions between NT and conventional tillage (CT) soil (Kaharabata et al. 2003; Lee et al. 2006; Melero et al. 2011). For example, the potential denitrification rates and the ratios of N₂O/N₂ were similar in NT and CT after harvesting in a rainfed crop rotation system in Spain (Melero et al. 2011). Others found that NT stimulates denitrification (Baudoin et al. 2009; Calderon et al. 2001; Wang and Zou 2020). The denitrification enzyme activity and denitrification gene abundances (*nirK* and *nosZ*) were enhanced in NT in a soybean/rice crop system in Madagascar (Baudoin et al. 2009). Similar results for the increase of denitrification gene abundance in NT was also observed under sub-zero temperatures (Tatti et al. 2015). The general trend that NT favored the denitrification rates, the abundance of denitrifying genes and N₂O emission was demonstrated at a global scale (Wang and Zou 2020).

Research has also addressed the differential consequences of tillage management on the microbial community structure and diversity. CT has a positive influence on the bacterial richness and diversity in clay soil in central Italy (Pastorelli et al. 2013). However, some studies found opposite results. Minimal tillage enriched the microbial population and diversity relative to CT in a recent global meta-analysis (Li et al. 2020). The bacteria diversity (represented by all the alpha-diversity indices) was higher in the NT soils compared to CT soils in a winter wheat cropping system in northern China (Dong et al. 2017). They also found that *Actinobacteria*, *Alphaproteobacteria*, *Gammaproteobacteria* and *Betaproteobacteria* were more abundant at class level in NT whereas CT had more sequences belong to *Acidobacteria*. In an experiment conducted in the agricultural fields in Indiana (USA), more DNA sequences related to the nitrogen metabolism were observed in the NT soils compared to CT soils, indicating the higher potential of nitrogen cycling (Smith et al. 2016).

Although researchers have previously studied the impacts of various agricultural management practices on denitrification and N₂O emission, the information on the taxonomic distributions and functional sequences related to nitrogen metabolism under different managements in the

field-crop ecosystems is still limited, especially in the U.S Midwest. The objective of this research was to investigate the impact of four agricultural management on the abundance and diversity of microbial communities regulating nitrogen cycling (primarily denitrification). The work focused on the agricultural sites at the Long Term Ecological Research (LTER) Site at Kellogg Biological Station (KBS), in southwest Michigan, southwest of the campus of Michigan State University (MSU). This LTER has field-crop ecosystems typical of the U.S. Midwest. The work is unique because it examines the key functional genes for nitrogen cycling over four long-term systems and detects a wider range of sequences through high throughput shotgun sequencing.

Methods

Sample Collection, DNA Extraction and Shotgun Sequencing

The DNA examined in the current work was generated from a previous study by our group (Thelusmond et al. 2019), involving an examination of the genes associated with xenobiotic biodegradation. Our previous work did not investigate the genes involved in nitrogen cycling. Briefly, four soils were collected from 5 sampling stations in 6 replicate plots for Treatments 1, 2, 3 and 4 within the Michigan State University Main Cropping System Experiment at Kellogg Biological Station Long-Term Ecological Research (KBS LTER) (42°24'N, 85°23'W). The agricultural management practices for each Treatment are illustrated in Table 1 and for additional information see <https://lter.kbs.msu.edu/research/site-description-and-maps/>. The physical and chemical characteristics of the soils were previously determined (A & L Great Lakes Laboratories, Inc., Fort Wayne, IN) with all being classified as loam soils. DNA extraction was completed using the DNA extraction kit (DNeasy PowerLyzer PowerSoil Kit, Mo Bio, USA) according to the manual protocol. Shotgun sequencing was performed with the Illumina HiSeq 4000 (2 × 150 bp) platform at the Research Technology Support Facility (RTSF) at Michigan State University (MSU), as previously described (Thelusmond et al. 2019).

Processing, DIAMOND Alignment, Diversity Analysis and Enrichments in Each Soil

Low quality sequences and Illumina adapters were removed from the HiSeq fastq.gz files using Trimmomatic with the Paired End Mode settings (Bolger et al. 2014) (Version 0.36). Protein

sequences for each of the nine genes were collected from the FunGene website (<http://fungene.cme.msu.edu/>) using a filter minimum HMM coverage of 70% (Cole et al. 2011; Fish et al. 2013). Following this, the FunGene Pipeline Dereplicator tool was used to derePLICATE these sequences (Cole et al. 2011; Fish et al. 2013). Table S1 provides a summary of the sequences obtained at each step.

The dereplicated sequences were then aligned against the trimmomatic files using DIAMOND (double index alignment of next-generation sequencing data) (Version 2.0.1) (Buchfink et al. 2015). Only reads that exhibited an identity of $\geq 60\%$ and an alignment length ≥ 49 amino acids to the reference sequences were retained. For each, relative abundance values were calculated using the number of aligned reads divided by the total number of sequences for each sample. The relative abundance values were then normalized by (divided by) the number of dereplicated reference sequences for each gene. Diversity indices (Chao 1, Chao2, Inverse Simpson and Shannon values) were determined (using the number of aligned reads for each gene) using EstimateS (Version 8.2.0) (Colwell 2006). The accession numbers of sequences statistically enriched in each soil (as described below) were determined. The R package Taxonomizr (Sherrill-Mix 2009) was used with R (Version 3.5.1) (R_Core_Team 2018) in RStudio (Version 0.9.24) (RStudio_Team 2020) to determine the taxonomic classification of each sequence. The data were illustrated with bar charts in Excel (Version 2010).

Phylogenetic Trees

The 50 most abundant sequences for each gene, averaged across all samples, were determined in Excel. The list of accession number for each were uploaded to COBALT: constraint-based alignment tool for multiple protein sequences (<https://www.ncbi.nlm.nih.gov/tools/cobalt/cobalt.cgi>) (Papadopoulos and Agarwala 2007). The downloaded alignments (fasta plus gaps) from COBALT were then submitted for MAFFT (multiple alignment using fast Fourier transform) alignment using an online server (<https://mafft.cbrc.jp/alignment/server/>) (Katoh et al. 2019) (Version 7). Trees, also obtained from the same website, by the Neighbor-Joining method were exported in Newick format. The downloaded tree files were uploaded to the Interactive Tree of Life (<https://itol.embl.de>) (Letunic

and Bork 2019) (Version 5.5.1). Sequences were colored depending on their classification and relative abundance values were added using the Datasets function called simple bar chart.

MG-RAST Analysis

Shotgun sequences were also analyzed by MG-RAST (Meta Genome Rapid Annotation using Subsystem Technology, Version 4.0.2) (Meyer et al. 2008). The processing pipeline includes removing artificial replicate sequences by dereplication and removing low quality sequencing by using SolexaQA (Cox et al. 2010). The taxonomic analysis included RefSeq (Pruitt et al. 2005) database and the KEGG (Kanehisa 2002) database. The sequences are available publicly on the MG-RAST and the summary of the MG-RAST data is presented in Table S2.

Statistical Analysis

RStudio was used to perform a number of statistical tests, as follows (Version 0.9.24) (RStudio_Team 2020). One-way ANOVA or Kruskal-Wallis tests were performed using the “aov” or “kruskal.test” functions as implemented in R package “car” (Fox et al. 2020) to determine if there were statistically significant differences between 1) relative abundance of functional genes obtained by DIAMOND and 2) richness and diversity values (Chao 1, Chao2, Inverse Simpson and Shannon values). First, Levene’s test was carried out to assess the homogeneity of variance of the data using the “leveneTest” function in the R package “car” (Fox et al. 2020). The Shapiro-Wilk test was conducted to evaluate the normality of the data using the “shapiro_test” function in the R package ‘rstatix’ (Kassambara 2020). When the p values from both of the Levene’s and the Shapiro-Wilk tests were more than 0.05, the differences between the means were determined by one-way ANOVA. When the p values from the one-way ANOVA were less than 0.05, multiple pairwise comparison between the means were performed using Tukey’s Honest Significant Difference test using the “TukeyHSD” function in the “stats” R package. When the p values from the Shapiro-Wilk test were less than 0.05, the non-parametric alternative to a one-way ANOVA, the test Kruskal-Wallis (function “kruskal.test” in the “stats” package), was used. When p values were less than 0.05 for the Kruskal-Wallis test, Dunn’s test, using the “dunnTest” function in the R package “FSA”, (Ogle et al. 2020)) was utilized to determine differences between means. Spearman’s Rank Correlation test was carried out to

explore the strength of correlation between the relative abundance of different genes using the “cor.test” function (with method = “spearman”) in the R package “stats”.

Principle component analysis (PCA) was performed within Microsoft Excel using XLSTAT (Addinsoft 2020) (Version 2020.3.1) to visualize the effect of the addition of pharmaceuticals on the gene relative abundance in different managed soils. STAMP (Statistical Analysis of Taxonomic and Functional Profiles, Version 2.1.3) (Parks et al. 2014) was used to statistically analyze the MG-RAST data. Specifically, extended error bars were generated to illustrate significant differences (Welch’s two-sided *t*-test, two group analysis option, $p < 0.05$) in the gene relative abundance for the genes associated with nitrogen metabolism (as defined by the KEGG hierarchy). The data (generated in MG-RAST, six metagenomes for each soil) were analyzed using STAMP with the two group analysis option (each soil compared to the other three soils) and Welch’s two sided *t*-test ($p < 0.05$).

Analysis of Assembled Sequences

Shotgun sequences processed by Trimmomatic were assembled with Megahit (Li et al. 2016) (Version 1.2.4) with the pair end plus single end option (minimum and maximum kmer size were 27 and 127 with a kmer size step of 10). TaxIds for the FunGene *nifH* database (as described above, except no dereplication occurred) were obtained with the R package taxonomizr (Sherrill-Mix 2009), RStudio (Team 2020) (Version 0.9.24) and R (Team 2018) (Version 3.5.1). The analysis targeted *nifH* because no significant differences were found between soils in the analysis described above (before assembly). Following the deletion of duplicate values, the taxids obtained were used to analyze the assembled reads using the NCBI nucleotide database (nt) with the taxids option in BLASTN (Altschul et al. 1990) (Version 2.10.0-Linux_x86_64). BLASTN command lines also included the following options: identity $\geq 60\%$, evalue $\leq 1 \times 10^{-5}$. The txt files generated from BLASTN were imported into Megan (Huson et al. 2016) (community edition Version 6.19.7). In Megan, the option “Compare” was used to combine all twenty-four data sets and then the combined dataset (at species level) was exported (using the STAMP export option) for analysis in STAMP. Additionally, the assembled contigs were aligned against the entire nt database using BLASTN without the taxids option (identity $\geq 60\%$, evalue $\leq 1 \times 10^{-5}$).

The output files were first imported and then in Megan, following this, the file was exported into STAMP to compare the communities between soils.

Results

Abundance and Diversity of Functional Genes

The relative abundance of genes associated with nitrogen fixation, denitrification or dissimilatory nitrate reduction in all four management systems are presented (Figure 1A), with the lowest abundance for *nifH* and highest for *nirK*. Two sets of genes were observed to have the approximately same level of abundance in the soils: the nitrate reductase genes *napA* and *narG*; and the nitrite reductase genes *nirA* and *nirB*. The distribution of the relative abundance of *nirK*, *norB* and *nosZ* were not as tightly grouped compared to the other genes, suggesting a greater spread in abundance of these genes across the metagenomes.

Principle component analysis of the functional genes (Figure 1B) indicated the nitrite reductase gene *nirK* was positively correlated with the nitrite reductase gene *nirS*, nitric oxide reductase gene *norB* and nitrous oxide reductase gene *nosZ*. Further, the nitrate reductase gene *napA* was positively correlated with the nitrite reductase gene *nirA*. In contrast, the nitrite reductase gene *nirB* did not appear to correlate with any other gene. The addition of pharmaceuticals impacted the functional genes in two treatments (conventional tillage and reduced input soils).

The average relative abundance of the twelve genes across the four management systems is displayed in Figure 2. Four genes (*nifH*, *nirK*, *nirS* and *norB*) were significantly lower in the NT treatment compared to one or more of the other treatments. The average relative abundance of *nirS* was significantly higher in the CT treatment compared to the other treatments. It was also interesting to note that the average relative abundance of *nosZ* was approximately 50% lower in the NT soil compared to the other soils, although the difference was not statistically confirmed. The results of the statistical analysis tests (Levene's test, Shapiro-Wilk, One-way ANOVA, Tukey's Honest Significant Difference, Kruskal-Wallis, Dunn's test) on these data sets are summarized (Tables S3-S5).

Figure 3 illustrates correlations between gene relative abundance percentages across all samples with all statistically significant positive correlations (Spearman's rank test) being boxed in red. The abundance *napA* significantly correlated with six genes (*narG*, *nirA*, *nirB*, *nirK*, *norB*, *nosZ*), as did the abundance of *narG* (*napA*, *nifH*, *nirA*, *nirB*, *nirK*, *norB*). In contrast, *nifH* correlated with two genes (*narG* and *nirK*). The abundance of both *nirA* and *nirB* correlated with *napA*, *narG* and to each other. Additionally, *nirK*, *nirS*, *norB*, *nosZ* all correlated positively to each other. The *p*-values and Spearman's correlation coefficients for the Spearman's rank tests are shown in Tables S6 & S7.

The values of richness estimators (Chao 1 and Chao 2) and diversity indexes (Shannon and Inverse Simpson) determined by EstimateS are summarized (Figure 4). The results of the statistical analysis (Levene's test, Shapiro-Wilk, One-way ANOVA, Tukey's Honest Significant Difference, Kruskal-Wallis, Dunn's test) on this data set are also summarized (Tables S8-S17).

Overall, higher Chao 1 and Chao2 values (~8000-9000) were found for four genes (*napA*, *narG*, *nirA*, *nirB*), whereas lower values (~500-1500) were estimated for the five other genes (*nifH*, *nirK*, *nirS*, *norB*, *nosZ*). For Chao 2 no significant differences were found between the four treatments for all genes. The only significant difference for Chao 1 between treatments was for *nirS*, *nirK* and *nifH*. Chao1 values were higher in both the CT treatment and the biological based treatment compared to the NT treatment for *nirS*. For *nirK*, Chao 1 was lower for the CT treatment compared to the reduced input treatment. For *nifH*, the Chao 1 value in the reduced input treatment was lower than the biological based treatment.

Overall, the average values for Shannon and Inverse Simpson were higher (~1000-2000 and ~7.2-8.1) for four genes (*napA*, *narG*, *nirA*, *nirB*) compared to the rest (~100-400 and ~5.4-6.4). For the Inverse Simpson values, at least one significant difference between treatments was noted for six genes (*napA*, *nirA*, *nirB*, *nirK*, *nirS*, *norB*), with the most notable number of differences between treatments being for *nirK*, *nirS* and *norB*. For *nirK* and *norB*, Inverse Simpson values were significantly higher in the NT treatment compared to the other treatments. For *nirA* and *nirB*, Inverse Simpson values were significantly higher in the reduced input treatment compared to the CT and NT treatments. For the Shannon Index values, at least one significant difference was found between at least two treatment for all genes except *nifH* and *nirB*. For *napA*, Shannon Index (and Inverse Simpson) values were significantly higher in the reduced input treatment

compared to the CT and NT treatments. For *nosZ*, Shannon values were significantly lower in CT treatment compared to the other treatments. It was also interesting to note that the Shannon values of *nirA* were higher in the reduced input treatment than in the conventional and no tillage treatments.

The abundance of the genes associated with the nitrogen metabolism (as defined in the KEGG hierarchy) were investigated to determine if there were significant differences between management systems. For this, each dataset was compared individually with the other three datasets (Figure 5). Only one gene (*norF*; nitric-oxide reductase NorF protein) was more abundant in the CT soil compared to the other three (Figure 5A). In contrast, six genes were more abundant in the NT soil compared to the other three soils (*nirA*; ferredoxin-nitrite reductase, *cynT*, *can*; carbonic anhydrase, nitronate monooxygenase, nitrate reductase (NADH), *nrfD*; protein NrfD and *hao*; hydroxylamine oxidase) (Figure 5B). Three genes (*nirB*; nitrite reductase (NAD(P)H) large subunit, *nosZ*; nitrous-oxide reductase, and *nirD*; nitrite reductase (NAD(P)H) small subunit (Figure 5C)) and one gene (nitronate monooxygenase) were dominant in the reduced input soil and biological based soil, respectively (Figure 5D).

Phylotypes Associated with Nitrogen Metabolism

The phylotypes (at the class level) associated with the nitrogen metabolism genes have been summarized (Figures 6 and 7). The CT soil was dominated by *Betaproteobacteria* for *napA*, *narG*, *nirA*, *nirB*, *nirK*, *nirS* and *norB* and by *Cytophagia* for *nosZ*. Further, in many cases (*napA*, *narG*, *nirA*, *nirB*, *nirK*, *norB*) *Betaproteobacteria* were more abundant in the CT soil compared to the other three soils. For several genes (*napA*, *narG*, *nirK*, *nosZ*), *Alphaproteobacteria* were more abundant in the NT soil compared to the other soils. While for *nirA* and *nirB*, *Alphaproteobacteria* were more abundant in the biological based soil compared to the other three soils. For the genes *napA*, *narG*, *nirK* and *norB*, *Actinobacteria* were more abundant in the NT soil compared to the other three soils. For *nirA* and *nirB*, *Actinobacteria* was approximately at the same level in biological based soil compared to the NT soil while somewhat lower in the conventional tillage and reduced input soils. Additional trends included the dominance of the *Gammaproteobacteria* for two of the four soils for *norB* as well as the dominance of unclassified sequences and *Flavobacteriia* across various soils for *nosZ*.

As no significant differences were noted for *nifH* for the above analysis, differences were investigated for this gene within the assembled contigs. Significant differences at the genera level associated with *nifH* gene between the CT and the other three soils are shown (Figure S1). The genus *Frankia* was significantly more abundant in the NT, reduced input and biological based soils compared to the CT soils. Several genera were enriched for this gene in the CT soil compared to the NT soil (e.g. *Rubrivivax*, *Leptothrix*, *Cupriavidus*). Also, two (*Paraburkholderia* and *Burkholderia*) were more enriched in the CT compared to the reduced input soils (Figure S1B). Four genera were more highly enriched in the comparison between the CT and the biological based soil for this gene (Figure S1C).

Comparison of Microbial Communities

When the entire microbial community from the assembled contigs was compared between treatments significant differences were found and are illustrated at the genus level (Figure S2). No enriched genera were found in the NT soil compared to the CT soil. Four genera (*Nocardioides*, *Mycobacterium*, *Nakamurella* and *Microvirga*) were enriched in both the reduced input and biological based compared to the CT soil. The other more abundant genera identified in the reduced input compared to the CT soil were *Pseudonocardia* and *Archangium*. The other enriched genera identified in the biological based compared to the CT soil included *Candidatus Nitrosotalea*, *Nitrospira*, *Bradyrhizobium*, *Actinoplanes*, *Nonomuraea*, *Skermanella*, *Sulfuritortus*, *Pigmentiphaga* and *Variibacter*.

Phylogeny of Most Abundant Sequences

The phylogenetic relationships of the representative sequences (fifty most abundant sequences, before contigs were assembled) for the genes related to nitrogen metabolism in the four soils are shown (Figure 8). The three most abundant sequences for *napA* and *narG* were the same sequences and classified as *Betaproteobacteria* and *Alphaproteobacteria*. Similarly, the three most abundant sequences for *nirA* and *nirB* were the same and belonged to *Deltaproteobacteria*, *Opitutae* and the unclassified. The three most abundant sequences for *norB* belonged to *Alphaproteobacteria* and were phylogenetically close to each other. For *nirK* and *nirS*, both the majority of the fifty most abundant sequences and the three most abundant sequences belonged to *Betaproteobacteria*. Moreover, the predominant representative sequences belonged to

Betaproteobacteria for *nirB*, *nirK* and *nirS* and belonged to *Alphaproteobacteria*, and *Flavobacteriia* for *nifH* and *nosZ*, respectively.

Discussion

The influence of different agricultural management practices on nitrogen metabolism is important for understanding N₂O emissions from agricultural soils. Here, the taxonomic and functional profiles of the soil microbial communities associated with nitrogen metabolism, primarily denitrification, were characterized in Mid-West agricultural soils under four different management practices. From the nine nitrogen metabolism genes examined in the soil metagenomes, the most abundant was *nirK*. Denitrifying microorganisms contain either a Cu-nitrite reductase or a cytochrome cd₁ nitrite reductase, encoded by *nirK* and *nirS* respectively (Zumft 1997). In the current study, *nirK* was approximately 17.9 times more abundant than *nirS* when all of the soil metagenomes were considered together. Further, consistent with other researchers, *nirK* and *nirS* gene abundance were significantly correlated (Enwall et al. 2010). Others have also reported higher levels of *nirK* compared to *nirS* in soil metagenomes, for example, *nirK* was up to 3.8 times more abundant than *nirS* in 35 from 37 soils (Jones et al. 2014). Additionally, *nirK* was more abundant compared to *nirS* during agricultural waste composting (Zhang et al. 2015a). In another study, *nirK* copy numbers were approximately two orders of magnitude higher than *nirS*, regardless of tillage treatment (Kim et al. 2021). These two genes are considered to be mutually exclusive, representing two ecologically distinct denitrifying communities (Enwall et al. 2010; Jones and Hallin 2010). To date, no microorganism has been reported to contain both types of reductases. It has been suggested that higher *nirS/nirK* ratios may indicate higher N₂O consumption trends (Jones et al. 2014). Based on this, in the current study, CT represents the highest N₂O consumption potential in four soils examined. Specifically, the average *nirS/nirK* ratios were 0.074, 0.045, 0.045 and 0.056 for CT, NT, reduced input and biological based, respectively.

Concerning other genes impacting N₂O depletion and formation, here, *nosZ* was less abundant compared to *norB* and (*nirK*+*nirS*). Others have also reported that *nir* gene abundance can exceed that of *nosZ* by up to one order of magnitude (Garcia-Lledo et al. 2011; Hallin et al. 2009; Philippot et al. 2011). This may be explained by the absence of *nosZ* in nearly one-third of genomes which contained *nir* and *nor* genes (Jones et al. 2008) and because *nosZ* has been found on plasmids (Zumft 1997).

When considering the different management practices, the abundance of *napA*, *narG*, *nifH*, *nirA* and *nirB* was not significantly different between NT and CT. The same trend was reported for *nifH* and *narG* by others (Liu et al. 2016). In contrast, we found that *nirK*, *nirS* and *norB* were statistically significantly lower in the NT compared to the CT treatment. Others have reported an increase in the abundance of denitrifying genes in response to NT (Baudoin et al. 2009; Wang and Zou 2020) or minimal tillage (Kaurin et al. 2018). However, in an experiment across arable soils, the abundance of *nirS*- and *nirK*- denitrifiers were not significantly different between agricultural practices (Domeignoz-Horta, Philippot et al. 2018). Similarly, in another study, the abundance of *nirK* and *nirS* did not differ between NT and CT (Puerta et al. 2019). The authors speculated that NT could have promoted denitrification in the form of higher activity but not the abundance of denitrifying genes. NT was reported to greatly increase the RNA/DNA ratios for *nirS* and *nosZ* denitrifiers (Tatti et al. 2015). They hypothesized that anoxic conditions (e.g., water content) contributed more to the *nirS* and *nosZ* transcription under NT compared to CT (Tatti et al. 2015). NT tends to reduce the oxygen level below the surface (Pastorelli et al. 2013) and increase the water-filled pore space because of greater soil moisture and bulk density (Wang and Zou 2020). These two factors may contribute to the potential enhanced anaerobic denitrification in NT soil. No correlation was found between denitrification enzyme activity and the abundances of *nirK*- and *nirS*- denitrifiers (Yin et al. 2014). More information is needed to determine the real impact of lower *nirK*, *nirS* and *norB* gene abundances in NT in the current system.

The microbial community richness (Chao1 and Chao2) and diversity (Shannon index and Inverse of Simpson) indices were generally higher for the genes associated with nitrate reduction (*napA* and *narG*) and dissimilatory nitrite reduction (*nirA* and *nirB*) compared to the other genes. For *nirK*, *norB* and *nosZ* for at least one and up to three richness and diversity indexes were

significantly greater in NT soil compared to CT soil, indicating a potential higher species richness and diversity in the current NT soil for these genes. In other research, higher alpha diversity of soil bacterial community was found in NT treatment compared to tilled treatment (Dong et al. 2017; Liu et al. 2020). Similarly, the richness and diversity of bacteria (characterized by phospholipid fatty acids analysis) were greater in NT over CT soil (Zhang et al. 2015b). This may be due to crop residues under the soil surface in NT soils being utilized as food sources (Zhang et al. 2015b). Another possible reason is that NT soil contains larger soil aggregates which could provide more organic matter for the microorganisms, therefore enhancing the bacterial diversity (Peixoto et al. 2006). It was demonstrated that denitrification activity was greatly influenced by denitrifier diversity but not the abundance. Using a dilution approach to manipulate the soil microbial community, researchers found that a decrease in the potential denitrification activity could be a result of denitrifier diversity loss and not the lower denitrifier biomass (Philippot et al. 2013). These trends could suggest that the NT examined in the current study may have a higher denitrification potential due to higher *norB* and *nosZ* diversity, although more research is needed to confirm this hypothesis.

It is interesting to note that Chao 1, Shannon and Inverse of Simpson were significantly higher in CT soil compared to NT soils for *nirS*. Inversely, for *nirK*, Shannon and Inverse of Simpson were significantly higher in NT soil over CT soil. A previous study reported that diversity indices targeting *nirS* were more sensitive to environmental factors compared to *nirK* (e.g., ammonium content, total organic carbon and total N) (Li et al. 2017). It was also found that *nirS*-denitrifiers rely more on the full anaerobic conditions than *nirK*-denitrifiers (Yuan et al. 2012). The greater diversity of *nirK* in NT in the current study could indicate oxygen levels and other environmental conditions in NT soil may be more favorable for *nirK*-denitrifiers than *nirS*-denitrifiers.

Several trends were noted concerning the taxonomy of the microorganisms associated with the functional genes studied. For example, the most abundant sequences classified within the *Proteobacteria* (primarily *Betaproteobacteria*) for *nirK* and *nirS*. Further, NT illustrated equal or more abundant levels of *Betaproteobacteria* (phylum *Proteobacteria*) compared to CT soil for a number of the genes examined (*nirK*, *nirS*, *norB* and *nosZ*). In other systems, *Betaproteobacteria* often dominates microbial populations due to high growth rates under available carbon substrates

(Jenkins et al. 2010). For *nifH*, *Frankia* (phylum *Actinobacteria*) was enriched in NT reduced input and biologically based soils compared to the CT soil. *Frankia* is a typical nitrogen-fixed organism both in free-living and symbiotic conditions (Sellstedt and Richau 2013).

Two phyla, *Actinobacteria* and *Acidobacteria*, were notably less enriched or absent in CT for several genes (*napA*, *narG*, *nirA*, *nirB* and *nirK*) compared to the other three soils. Relating these results to previous research, others have examined soil microbial communities under different management systems. For example, one-time tillage increased the abundance of *Actinobacteria* and *Acidobacteria* in an acidic Solonetz with a 19-year NT management in Australia (Liu et al. 2016). In another study, the abundance of *Acidobacteria* was higher in CT over NT, with the pH of 7.4 and 7.5, respectively (Dong et al. 2017). *Acidobacteria* are acidophilic and could be favored by slightly to moderately acidic growth conditions (Sait et al. 2006). Moreover, *Acidobacteria* exhibit the functional ability of the degradation of plant-derived organic matter (Naumoff and Dedysh 2012) and thus play an important role in the decomposition of organic matter (Rampelotto et al. 2013).

For *nosZ*, the most abundant sequences belonged to the *Bacteroidetes* (with the dominant class of *Flavobacteria*). Others have reported *Bacteroidetes* display copiotrophic characteristics and are favored by increased nutrient availability (McHugh and Schwartz 2015). We found *Flavobacteria* was absent in NT soil but dominated in CT soil for *nosZ*. Consistent with these results, microbial community studies have reported more *Bacteroidetes* in CT compared to NT soil (Yin et al. 2017). *Bacteroidetes* were also more dominant in one soil compared to the same soil under non-disturbed grass systems (Acosta-Martinez et al. 2008). However, others have reported that *Bacteroidetes* were more abundant under NT compared to CT in winter wheat cropping system (Dong et al. 2017) and non-disturbed grass system in comparison with agricultural rotation system (Zhang et al. 2014). Besides, NT increased the abundance of *Flavobacteria* compared to the tilled treatment under semi-arid conditions (Liu et al. 2020). Notably, the above studies did not examine the taxonomy of the microorganisms linked with *nosZ* and so it is difficult to conclude if our results are typical of NT compared to CT soils.

Recommended future research to build on the current genomic analysis should include correlations between gene and transcript counts and nitrous oxide emissions. As with all molecular methods, the genomic analysis approach used in the current work has several notable

limitations. One shortcoming involves the analysis of genomic DNA rather than messenger RNA, which would indicate actual activity instead of potential activity. Future research involving transcriptomics to confirm the results of the current study would be beneficial. Additionally, the results obtained are dependent on the analysis thresholds for example, protein sequences for each of the nine genes were collected from the FunGene using a filter minimum HMM coverage of 70%. Increasing or decreasing this threshold would have impacted the downstream analysis. Also, changes in the read alignment identity (set at $\geq 60\%$) and alignment length (≥ 49 amino acids) will also effect the results obtained. It is also important to note that the current analysis did not involve nitrification enzymes, which are also highly relevant for an understanding of nitrous oxide emissions.

In conclusion, the agricultural management practices investigated here impacted gene abundance as well as the taxonomy of microorganisms associated with the nitrogen metabolism. From the nine genes examined, *nirK* was the most abundant and *nifH* was the least abundant. The *nirS/nirK* ratios were highest for the CT system, which may indicate a greater potential for N₂O consumption. Three genes (*nirK*, *nirS* and *norB*) were statistically significantly lower in the NT compared to the CT treatment. The microbial community richness and diversity indices were generally higher for the genes associated with nitrate reduction (*napA* and *narG*) and dissimilatory nitrite reduction (*nirA* and *nirB*) compared to the other genes. For *nirK*, *norB* and *nosZ* a number of the richness and diversity indexes were significantly greater in NT soil compared to CT soil, indicating a potentially a higher denitrification potential. A number of trends were noted for the taxonomy of the functional genes across agricultural systems. The genus *Frankia* was significantly more abundant in the NT, reduced input and biological based soils compared to the CT soils. The CT soil was dominated by *Betaproteobacteria* for seven genes and by *Cytophagia* for *nosZ*. Also, for six of these genes, *Betaproteobacteria* were more abundant in the CT soil compared to the other three soils. *Alphaproteobacteria* were more abundant in the NT soil compared to the other soils for several genes. While for *nirA* and *nirB*, *Alphaproteobacteria* were more abundant in the biological based soil compared to the other three soils. For *napA*, *narG*, *nirK* and *norB*, *Actinobacteria* were more abundant in the NT soil compared to the other three soils. Overall, these results suggest microbial communities involved in nitrogen metabolism are sensitive to varying soil conditions, which in turn, likely has important implications for N₂O emissions.

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Authors' contributions

AC and ZL conceived and designed research. AC and ZL analyzed the data. ZL wrote the manuscript and AC edited the manuscript. All authors read and approved the manuscript.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available on the MG-RAST website (details for the MG-RAST data can be found in Table S2).

Compliance with ethical standards

Conflict of interest

All authors declare no conflict of interest.

Ethical statement

This work was, in part, supported by USDA (Agriculture and Food Research Initiative, Number 2014-67024) and KBS LTER (Kellogg Biological Station Long-Term Ecological Research).

Human and animal rights and informed consent

This article does not contain any studies with human participants or animals performed by any of the authors

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Zumft WG (1997) Cell biology and molecular basis of denitrification. Micro Mol Biol Rev 61(4):533-+ doi:10.1128/.61.4.533-616.1997

Table and Figure Legends

Table 1. Summary of the KBS agricultural management approaches for the four soils examined.

Figure 1. Box and whisker plot of relative abundance of genes (A) and Principle Component Analysis of the genes across the four management practices (with or without pharmaceuticals added) (B).

Figure 2. Average relative abundance values (% , as determined by DIAMOND) for each soil ($n=6$) with standard deviations illustrated with the bars. Values that are statistically significantly different (ANOVA or Kruskal-Wallis test, $p<0.05$) are shown with different letters. Letters are missing for *nosZ* because the statistical assumptions were not met for either test (unequal variance). Note, all y-axis have different scales.

Figure 3. Scatterplots comparing relative abundance values of all genes across all samples. Correlations that were statistically significant (Spearman's rank test, $p<0.05$) are boxed in red.

Figure 4. Average index diversity values and richness estimators for each soil (as determined by EstimateS, $n=6$) with standard deviations. Values that are statistically significantly different (ANOVA or Kruskal-Wallis test, $p<0.05$) are shown with different letters. In some cases, letters are missing because the statistical assumptions were not met for either test. Note, the scale on the y-axis differs between graphs.

Figure 5. Extended error bars illustrating the differences between each treatment compared to the other three treatments for the genes associated with nitrogen metabolism (as defined by the KEGG hierarchy). The data (generated in MG-RAST, six metagenomes for each soil) were analyzed using STAMP with the two group analysis option (each soil compared to the other three soils) and Welch's two sided t-test ($p<0.05$).

Figure 6. Phylotypes enriched in each soil associated with the genes *napA*, *narG*, *nirA* and *nirB* at the level of class. All y-axis have the same scale.

Figure 7. Phylotypes enriched in each soil associated with the genes *nirK*, *nirS*, *norB* and *nosZ* at the level of class. Note, the y-axis scales on each are different. There was minimal enrichment for any soil for *nifH*, therefore no graph was generated.

Figure 8. Neighbour-Joining phylogenetic trees of fifty most abundant sequences in each soil associated with the genes *napA*, *narG*, *nifH*, *nirA*, *nirB*, *nirK*, *nirS*, *norB* and *nosZ*. Note, the bar charts illustrate the relative abundance (%) of the sequences in each soil. The three most abundant sequences are highlighted in yellow.

The legends for the tables and figures are listed after the references in the manuscript document (as requested by the journal)

Table 1.

Conventional	This system is practiced by most farmers in this region. Tilled corn–soybean–winter wheat (c–s–w) rotation; standard chemical inputs, chisel-plowed, no cover crops, no manure or compost
No-till	No-till c–s–w rotation; standard chemical inputs, permanent no-till, no cover crops, no manure or compost
Reduced Input	Biologically based c–s–w rotation managed to reduce synthetic chemical inputs; chisel-plowed, winter cover crop of red clover or annual rye, no manure or compost
Biologically Based	Biologically based c–s–w rotation managed without synthetic chemical inputs; chisel-plowed, mechanical weed control, winter cover crop of red clover or annual rye, no manure or compost; USDA-certified organic

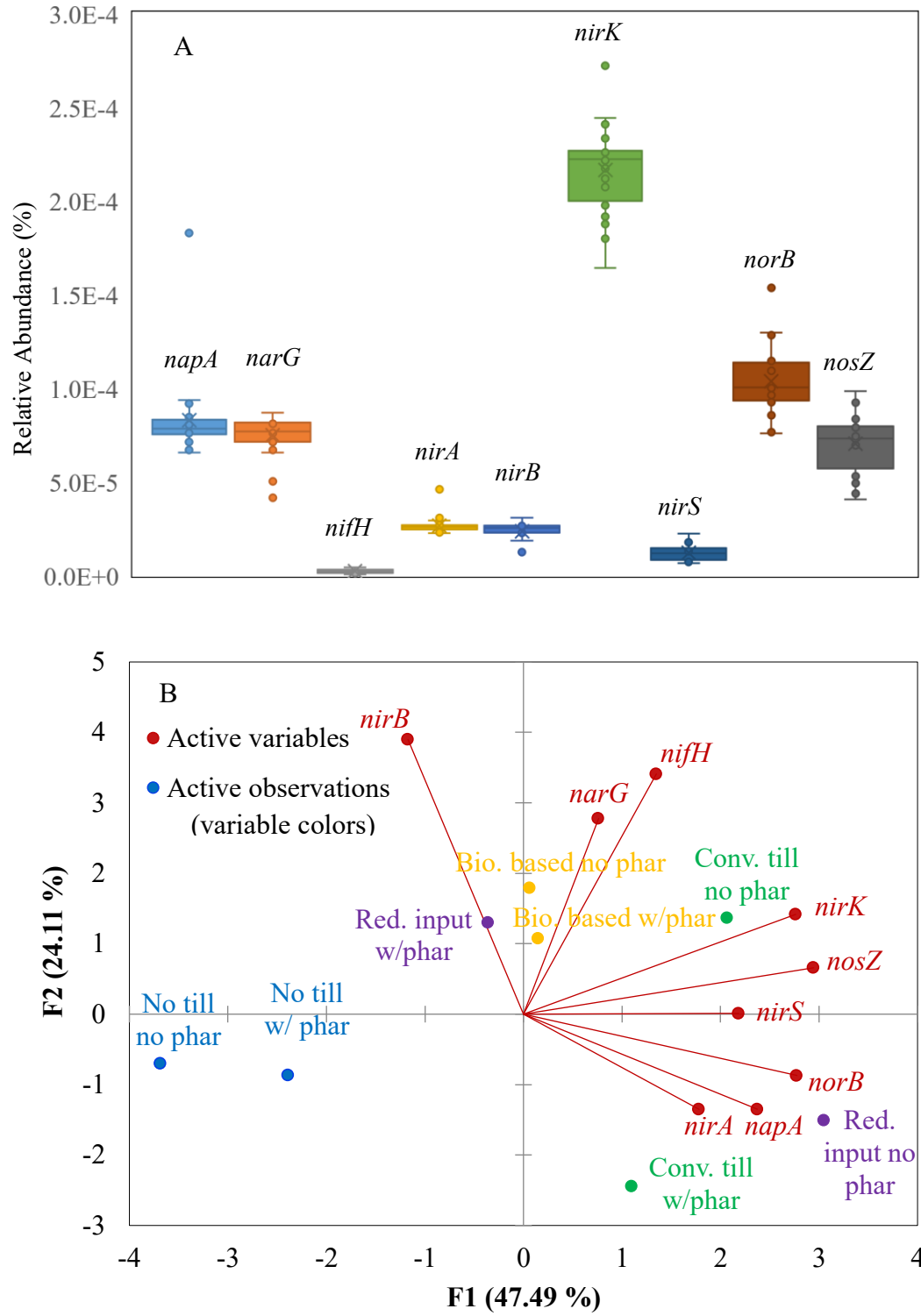


Figure 1.

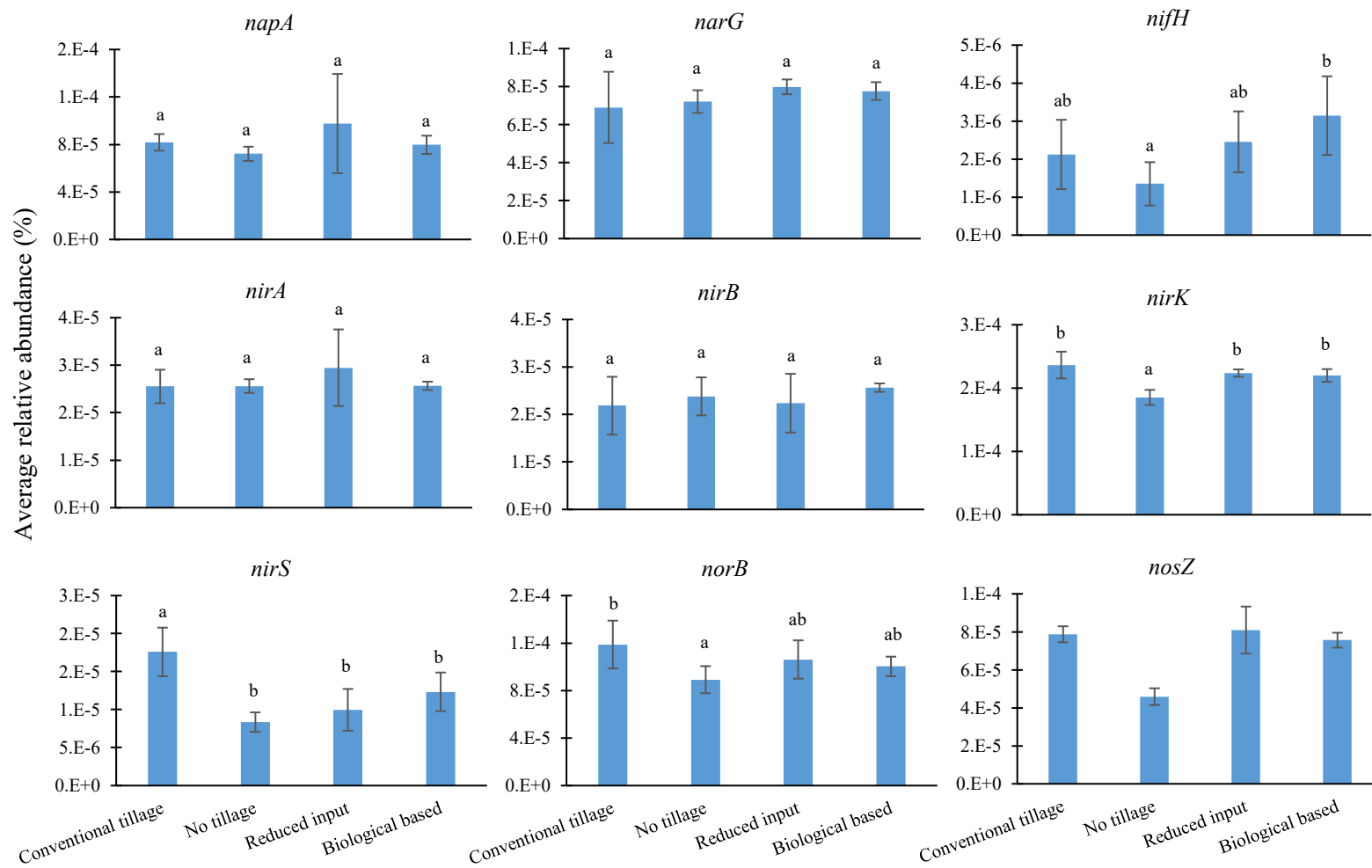


Figure 2.

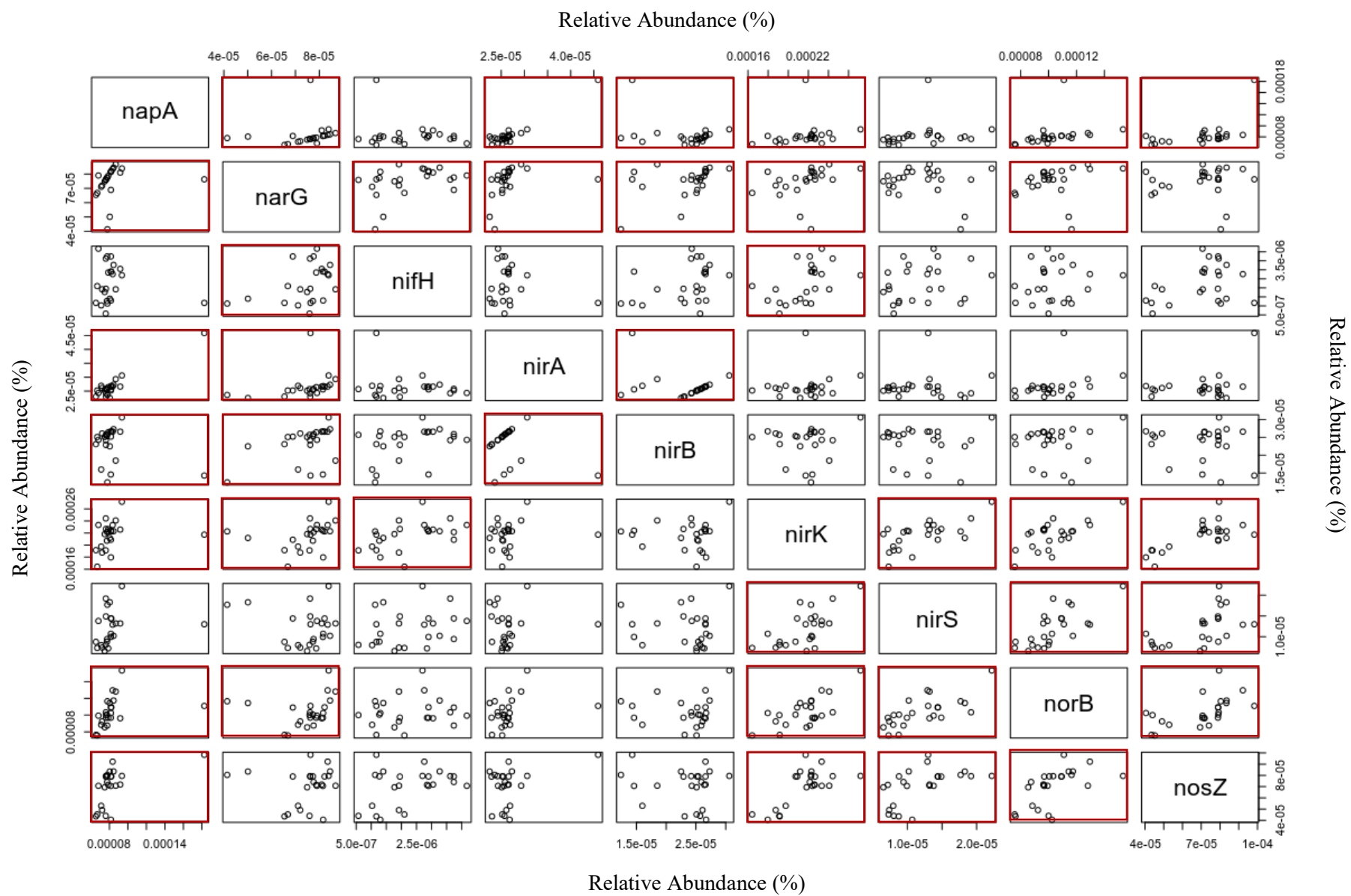


Figure 3.

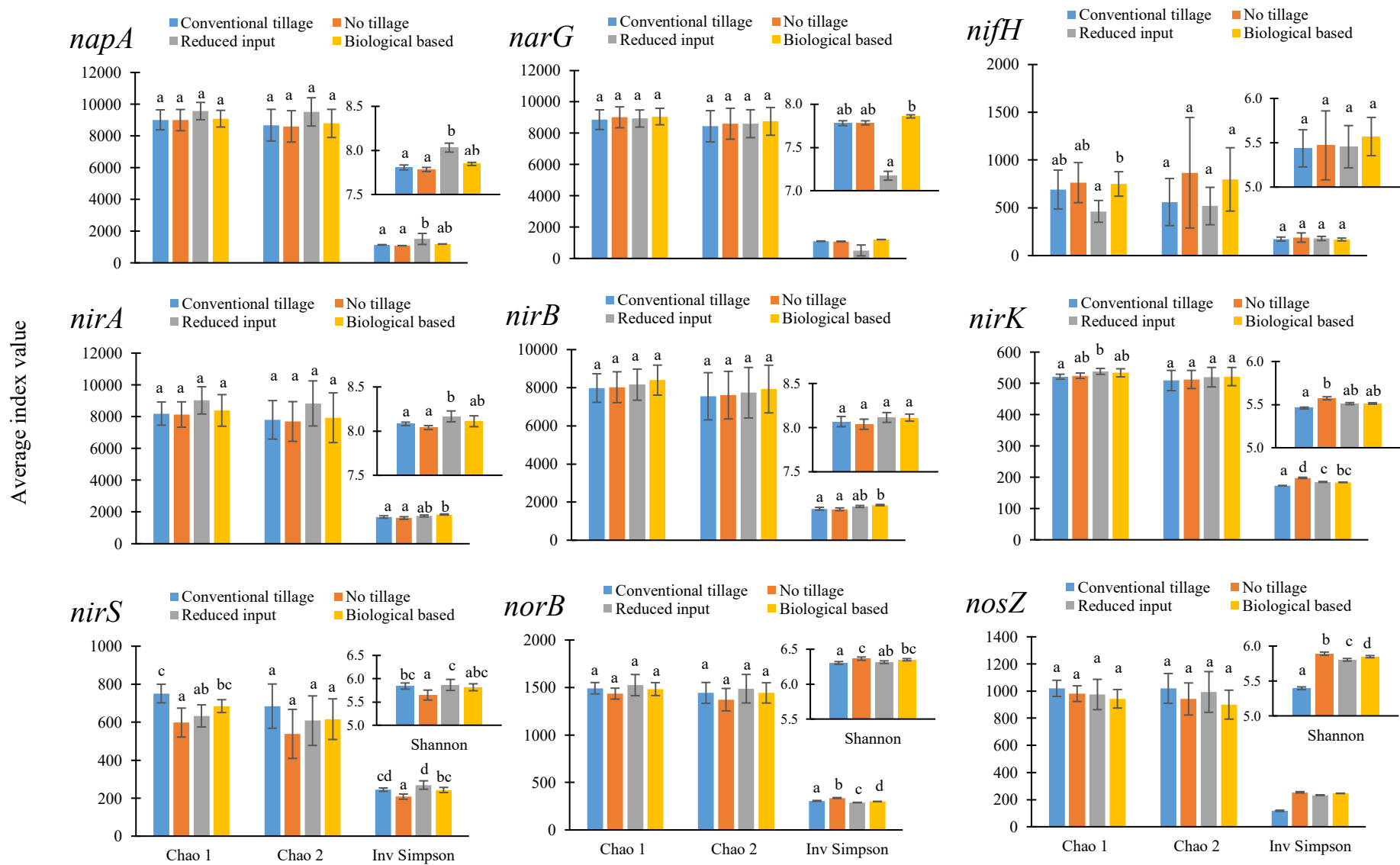
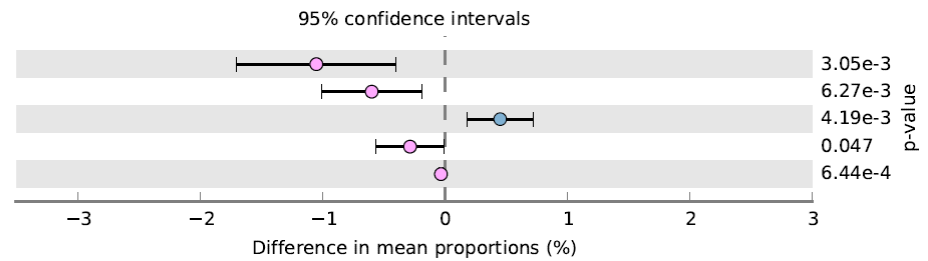
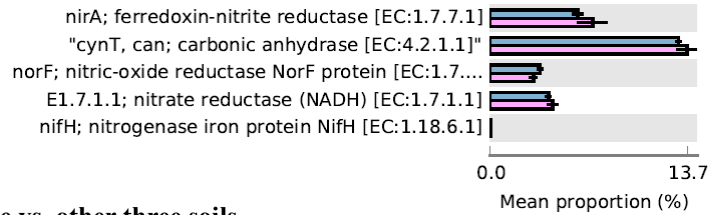
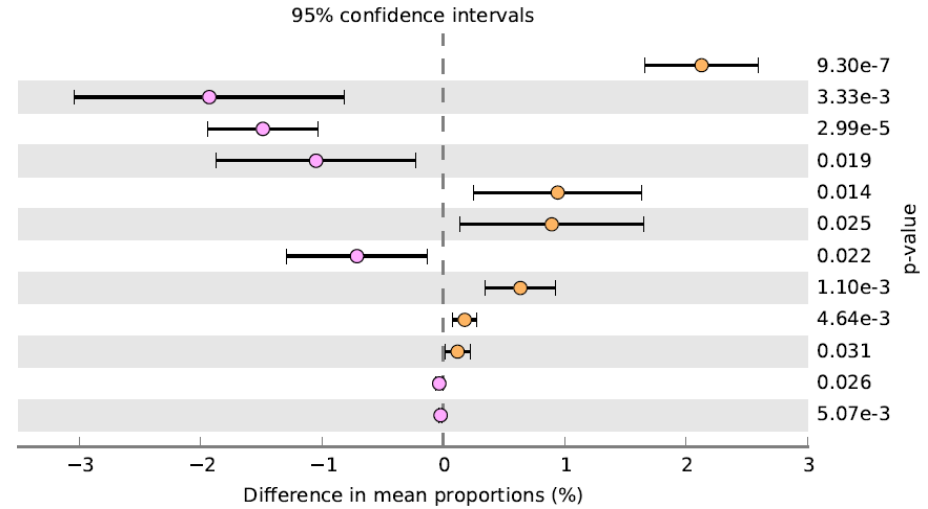
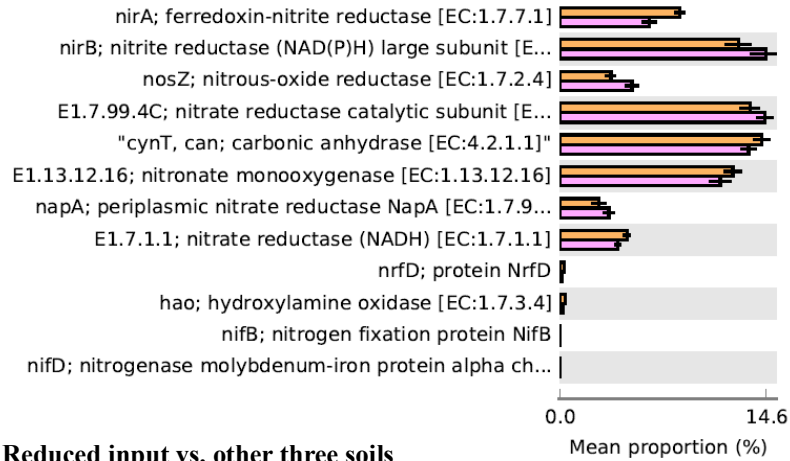


Figure 4.

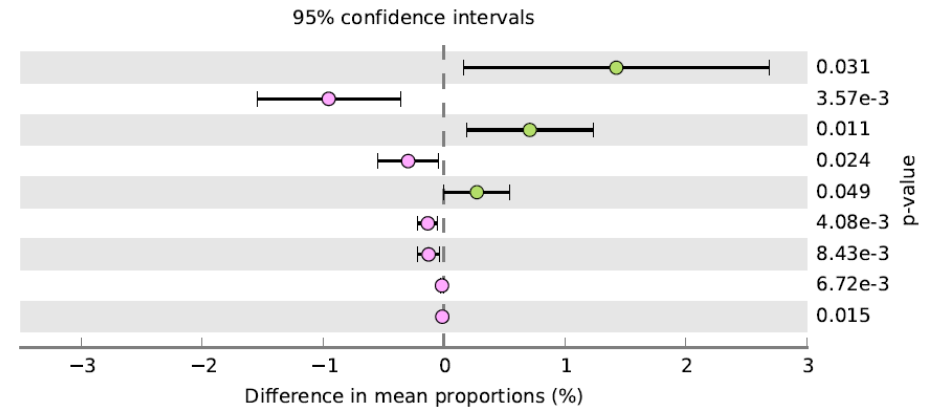
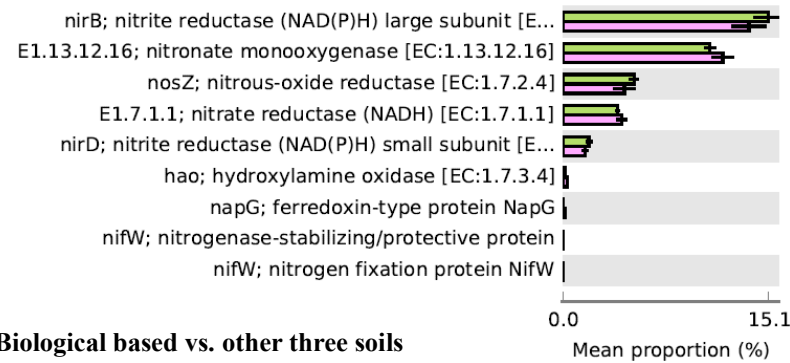
Conventional tillage vs. other three soils



No tillage vs. other three soils



Reduced input vs. other three soils



Biological based vs. other three soils

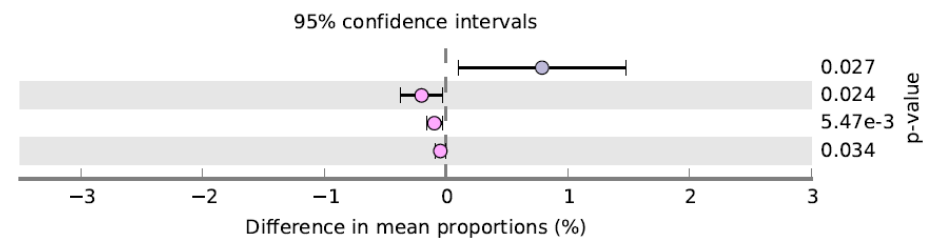
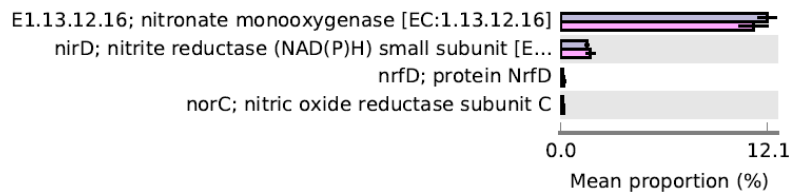


Figure 5.

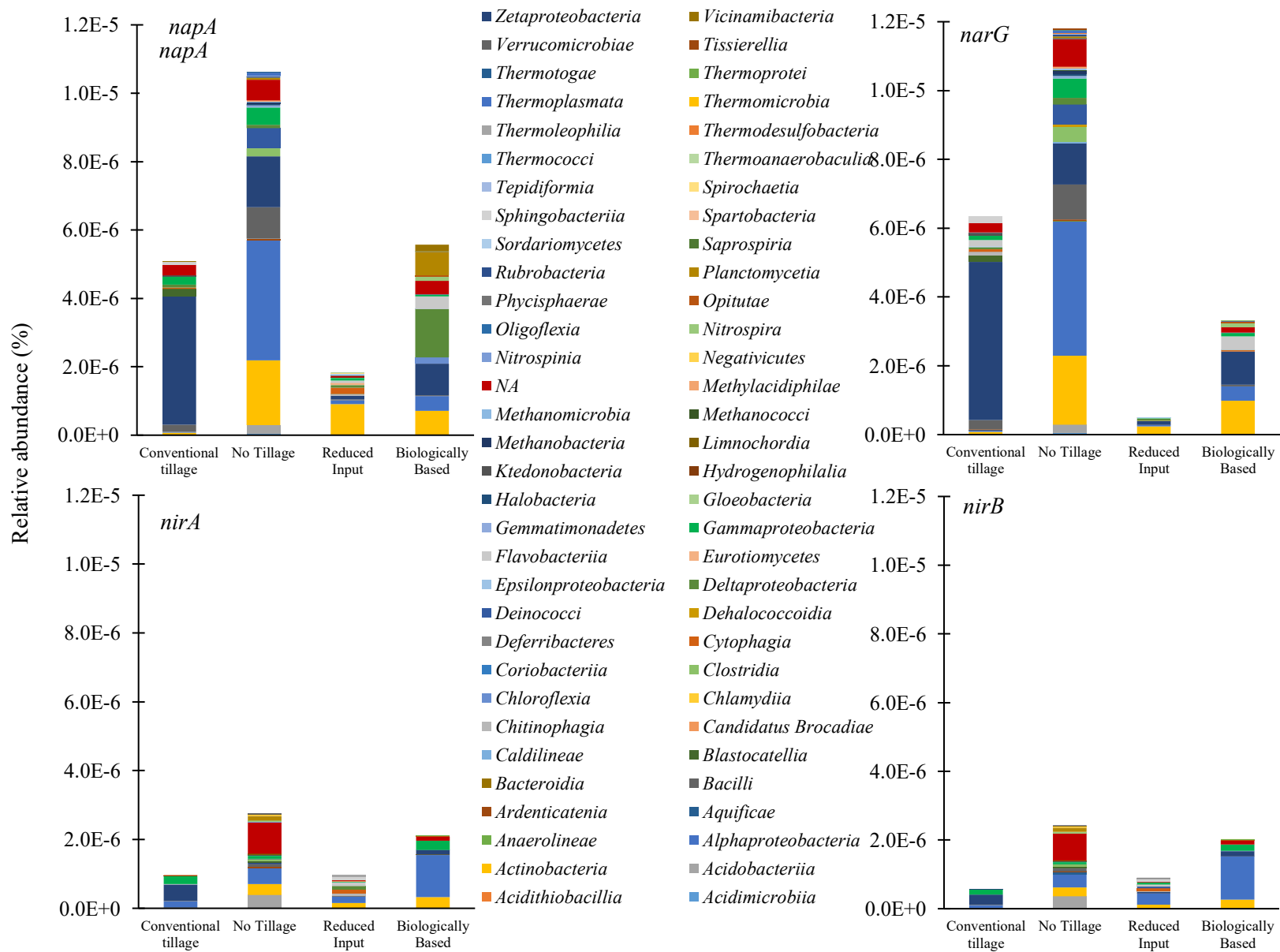


Figure 6.

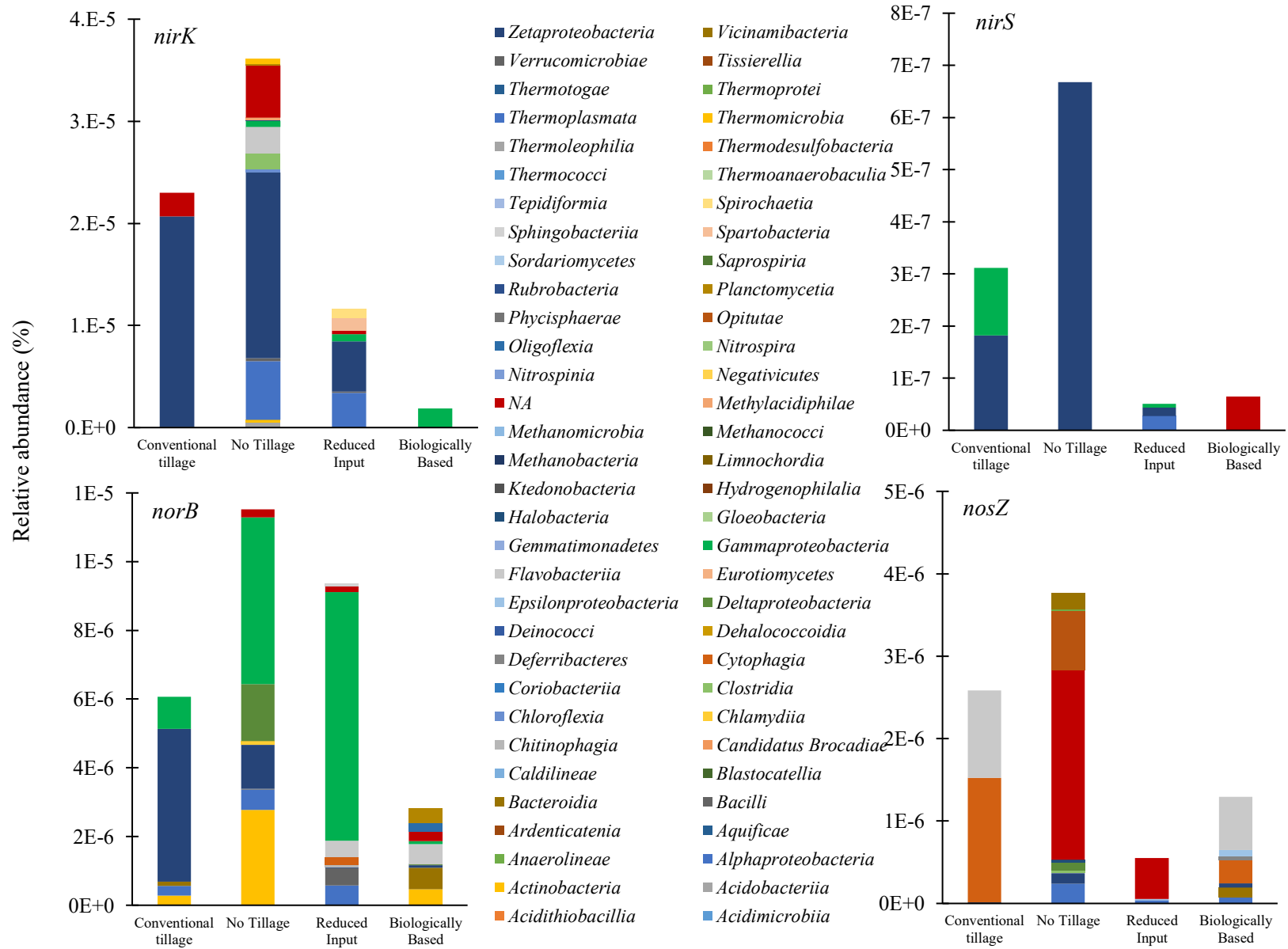
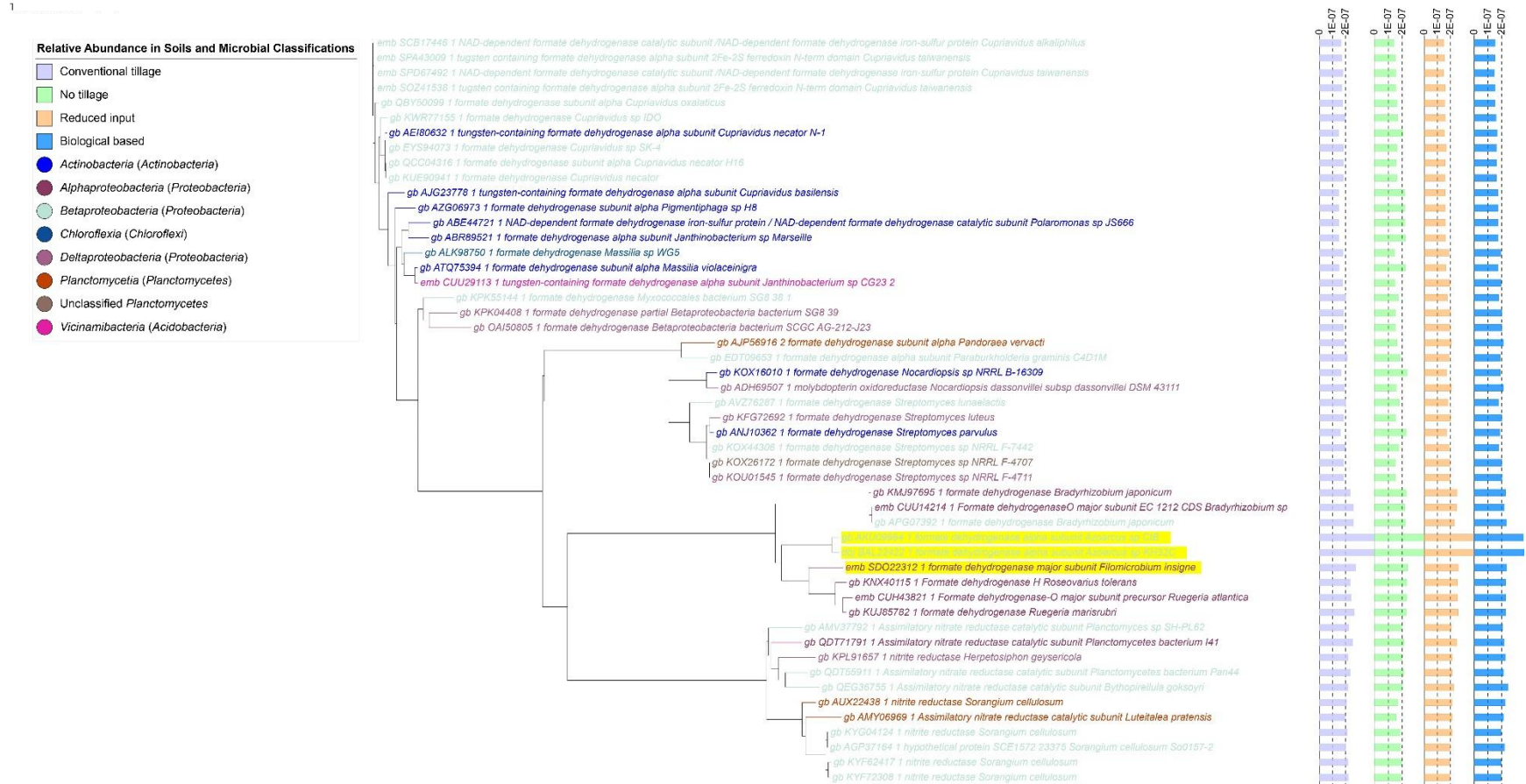


Figure 7.

(1) *napA*

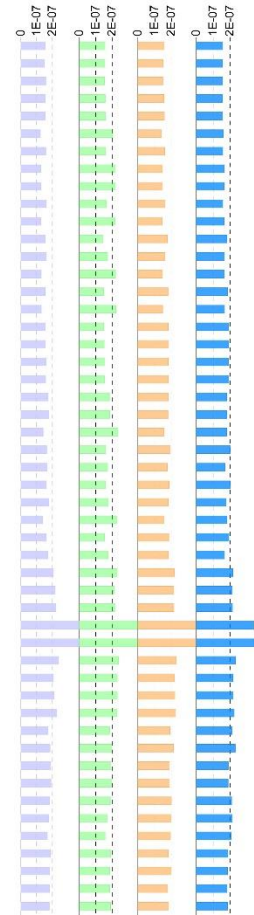


(2) *narG*

Tree scale: 0.1

Relative Abundance in Soils and Microbial Classifications

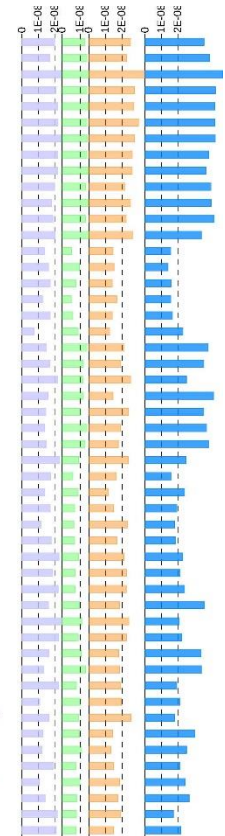
- Conventional tillage
- No tillage
- Reduced input
- Biological based
- Actinobacteria (Actinobacteria)
- Alphaproteobacteria (Proteobacteria)
- Betaproteobacteria (Proteobacteria)
- Chloroflexia (Chloroflexia)
- Deltaproteobacteria (Proteobacteria)
- Planctomycetia (Planctomycetes)
- Unclassified Planctomycetes
- Vicinamibacteria (Acidobacteria)



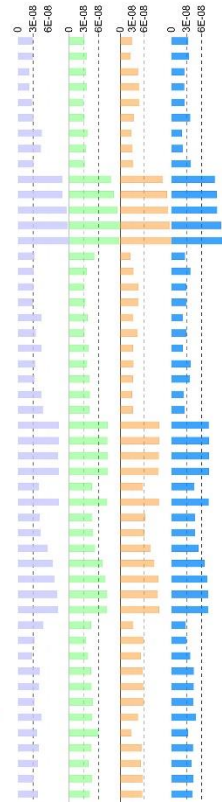
(3) *nifH*

Tree scale: 0.1

Relative Abundance in Soils and Microbial Classifications



Tree scale: 0.1

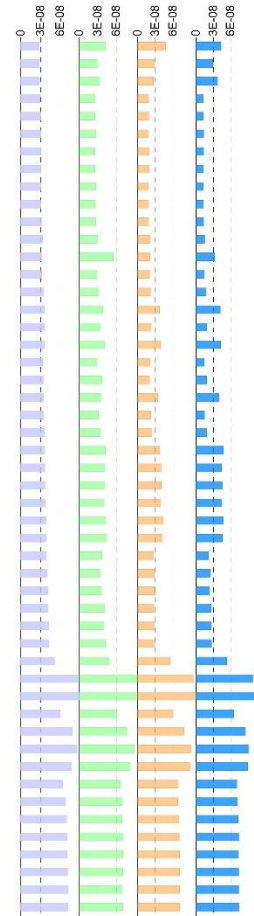
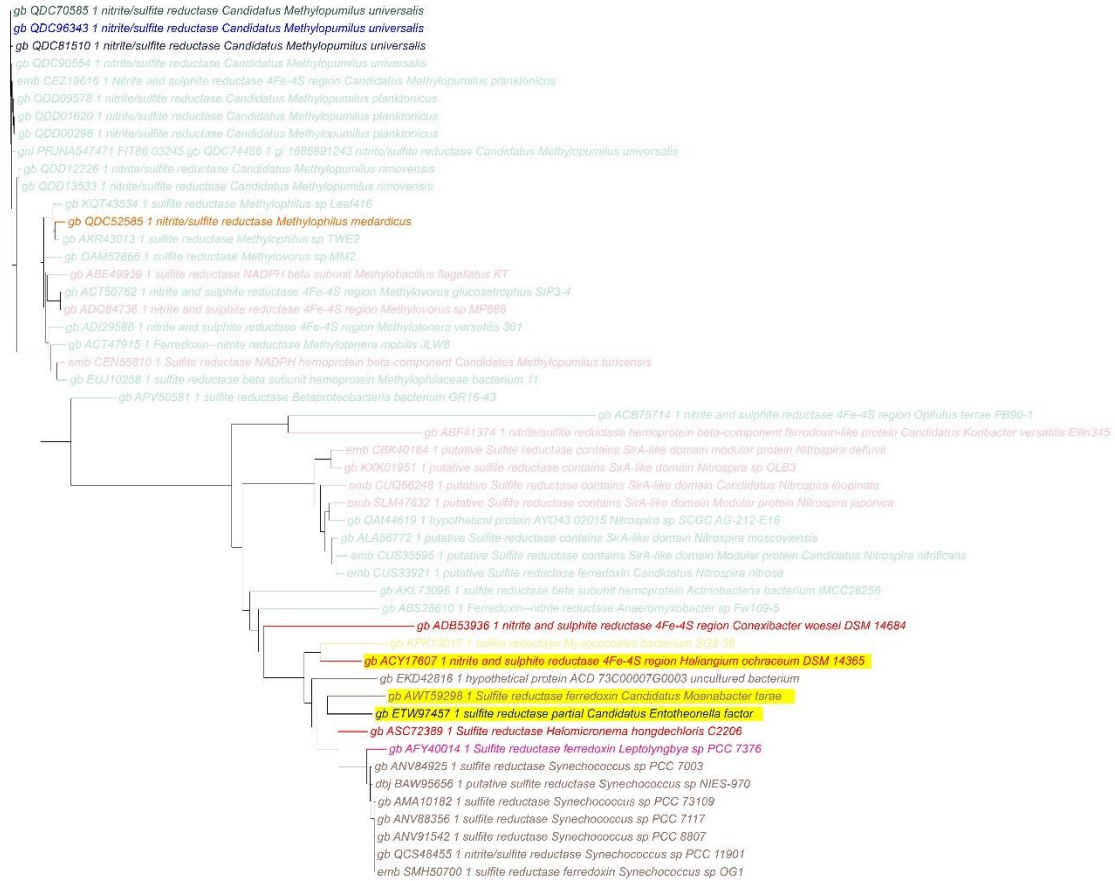


(5) *nirB*

Tree scale: 0.1

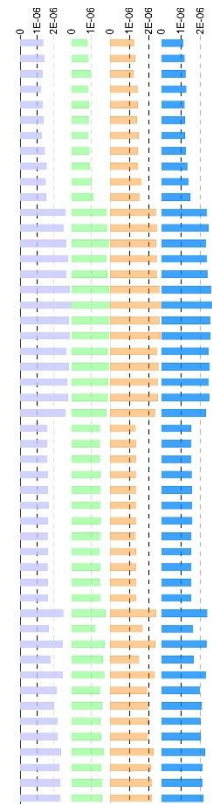
Relative Abundance in Soils and Microbial Classifications

- Conventional tillage
- No tillage
- Reduced input
- Biological based
- Acidobacteria (Acidobacteria)
- Actinobacteria (Actinobacteria)
- Betaproteobacteria (Proteobacteria)
- Deltaproteobacteria (Proteobacteria)
- Nitrospira (Nitrospirae)
- Opitutae (Verrucomicrobia)
- Thermoleophila (Actinobacteria)
- Unclassified (Candidate Tectomicrobia)
- Unclassified (Cyanobacteria)
- Unclassified



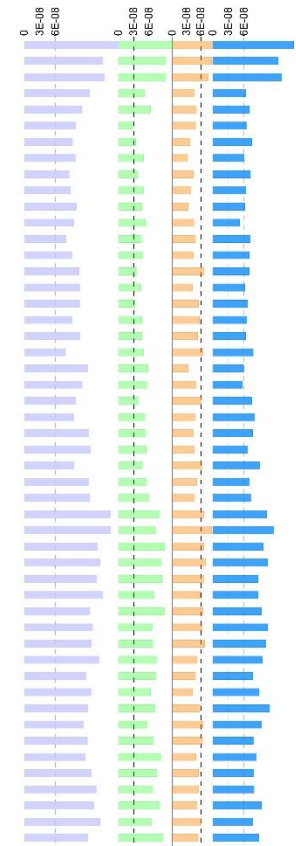
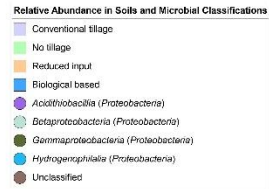
(6) *nirK*

Tree scale: 0.1



(7) *nirS*

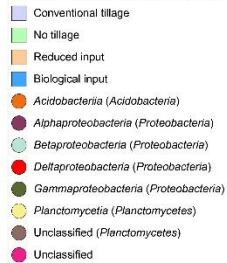
Tree scale: 0.1



(8) *norB*

Tree scale: 0.1

Relative Abundance in Soils and Microbial Classifications



(9) *nosZ*

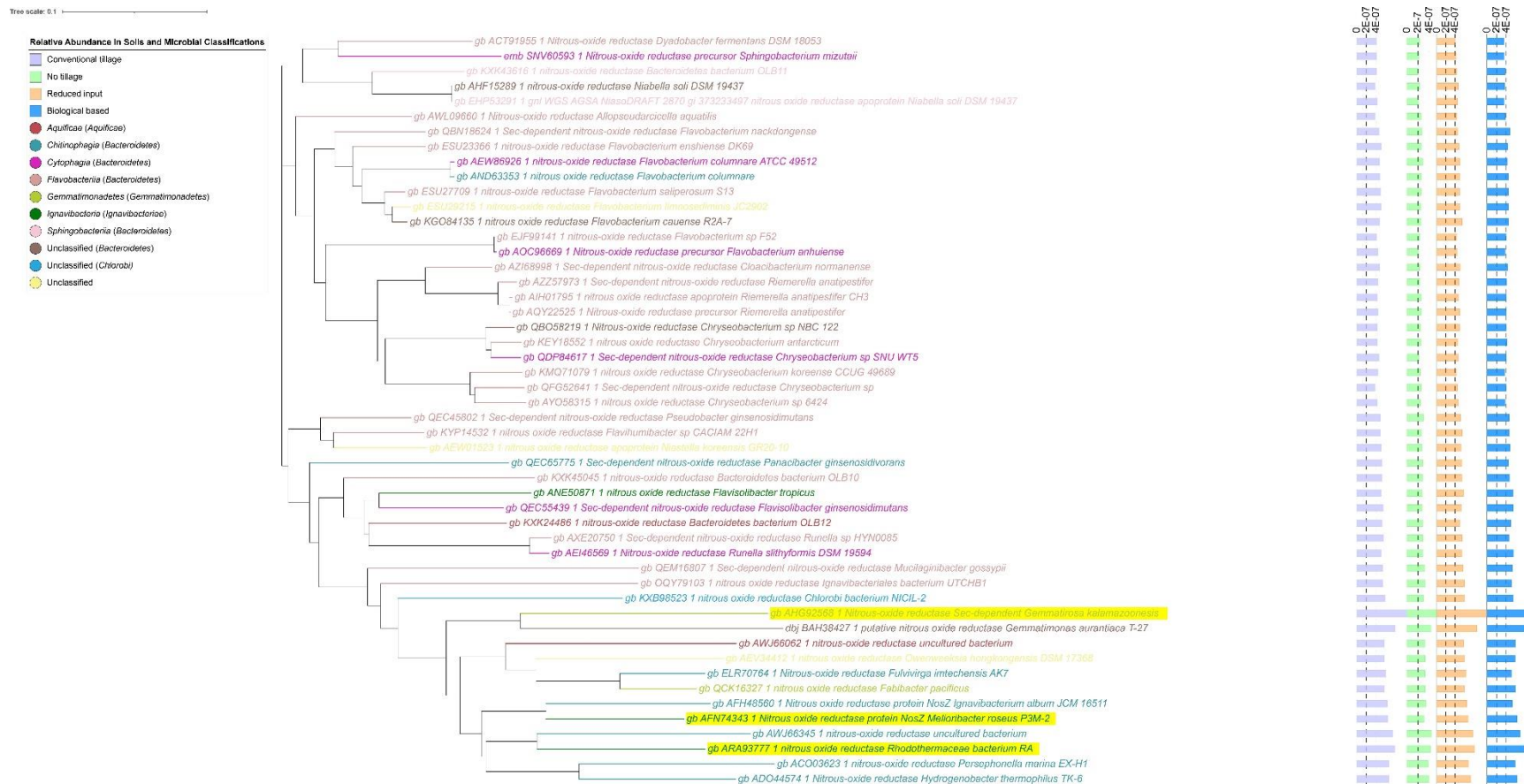


Figure 8.

Applied Microbiology and Biotechnology

Supplementary Section

Diversity of Nitrogen Cycling Genes at a Midwest Long Term Ecological Research Site with Different Management Practices

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Table S1. FunGene and DIAMOND sequence data summary.

	On FunGene	Minimum HMM Coverage 70%	Dereplicated
<i>napA</i>	74937	40226	11395
<i>narG</i>	50753	49174	11395
<i>nosZ</i>	5304	3787	1266
<i>norB</i>	13238	7054	1778
<i>nifH</i>	19514	3474	1562
<i>nirK</i>	7988	3367	556
<i>nirS</i>	25330	3020	993
<i>nirA</i>	54085	51514	12955
<i>nirB</i>	90760	45767	12955

Table S2 MG-RAST sequence data summary.

Soil type	MG-RAST ID	Post QC: bp Count	Post QC: Sequences Count	Post QC: Mean Sequence Length bp
Conventional tillage	mgm4887245.3	1,049,991,462 bp	4,562,115	230 ± 37 bp
Conventional tillage	mgm4889385.3	865,087,512 bp	3,773,767	229 ± 38 bp
Conventional tillage	mgm4887247.3	873,760,585 bp	3,805,693	230 ± 38 bp
Conventional tillage	mgm4887261.3	1,042,733,021 bp	4,497,130	232 ± 37 bp
Conventional tillage	mgm4887259.3	1,186,811,683 bp	5,171,096	230 ± 37 bp
Conventional tillage	mgm4887263.3	1,049,806,246 bp	4,606,628	228 ± 38 bp
No tillage	mgm4887248.3	978,574,572 bp	4,289,260	228 ± 38 bp
No tillage	mgm4887249.3	1,021,883,457 bp	4,491,203	228 ± 38 bp
No tillage	mgm4887251.3	893,615,124 bp	3,901,326	229 ± 38 bp
No tillage	mgm4887262.3	1,052,482,005 bp	4,556,161	231 ± 37 bp
No tillage	mgm4887265.3	1,171,824,030 bp	5,106,093	229 ± 37 bp
No tillage	mgm4887264.3	1,151,447,486 bp	5,131,392	224 ± 39 bp
Reduced input	mgm4887252.3	1,020,227,225 bp	4,473,295	228 ± 38 bp
Reduced input	mgm4887253.3	1,156,421,815 bp	5,084,544	227 ± 38 bp
Reduced input	mgm4887254.3	845,604,740 bp	3,689,278	229 ± 38 bp
Reduced input	mgm4887267.3	904,740,521 bp	3,896,151	232 ± 37 bp
Reduced input	mgm4887266.3	1,216,560,266 bp	5,320,030	229 ± 38 bp
Reduced input	mgm4887268.3	923,078,351 bp	4,016,875	230 ± 37 bp
Biological based	mgm4887255.3	1,070,768,940 bp	4,666,479	229 ± 38 bp
Biological based	mgm4887256.3	1,048,398,089 bp	4,589,220	228 ± 38 bp
Biological based	mgm4887258.3	1,095,942,092 bp	4,834,482	227 ± 38 bp
Biological based	mgm4887270.3	1,410,382,064 bp	6,169,872	229 ± 38 bp
Biological based	mgm4887289.3	1,149,249,456 bp	5,008,186	229 ± 37 bp
Biological based	mgm4887290.3	1,303,754,397 bp	5,670,793	230 ± 37 bp

Table S3. P-values for statistical tests with the relative abundance of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Shapiro-Wilk test				Levene's test	One-way ANOVA	Kruskal-Wallis test
Null Hypothesis	The sample distribution is normal				$\sigma_1 = \sigma_2$	$\mu_1 = \mu_2$	Median ₁ = Median ₂
Soil groups	Conventional tillage	No tillage	Reduced input	Biological based			
<i>napA</i>	1.57E-01	7.77E-01	2.50E-04	7.69E-01	5.35E-01	N/A	6.02E-02
<i>narG</i>	1.59E-01	7.66E-01	6.31E-01	1.71E-01	9.14E-02	2.74E-01	N/A
<i>nifH</i>	6.03E-01	7.31E-01	2.20E-01	2.44E-01	8.27E-01	1.26E-02	N/A
<i>nirA</i>	7.19E-02	2.20E-01	3.40E-04	5.73E-01	5.45E-01	N/A	4.81E-01
<i>nirB</i>	8.65E-01	2.11E-02	1.34E-02	5.69E-01	3.49E-01	N/A	4.09E-01
<i>nirK</i>	7.12E-01	3.27E-01	6.55E-01	5.24E-01	1.33E-01	1.61E-05	N/A
<i>nirS</i>	9.31E-01	1.16E-01	3.44E-01	4.63E-02	4.37E-01	2.22E-05	N/A
<i>norB</i>	5.97E-01	3.68E-01	8.43E-01	5.68E-01	3.81E-01	1.85E-02	N/A
<i>nosZ</i>	N/A	N/A	N/A	N/A	5.81E-03	N/A	N/A

Table S4. P-values for Tukey HSD test with the relative abundance of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Tukey's HSD test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	4.14E-01	N/A	N/A	1.14E-05	2.07E-05	1.16E-02	N/A
Conventional tillage - Reduced input	N/A	N/A	9.03E-01	N/A	N/A	3.84E-01	2.33E-04	4.65E-01	N/A
Conventional tillage - Biological based	N/A	N/A	1.89E-01	N/A	N/A	1.79E-01	9.27E-03	1.65E-01	N/A
No tillage - Reduced input	N/A	N/A	1.42E-01	N/A	N/A	4.10E-04	6.94E-01	2.22E-01	N/A
No tillage- Biological based	N/A	N/A	7.59E-03	N/A	N/A	1.26E-03	5.82E-02	5.68E-01	N/A
Reduced input - Biological based	N/A	N/A	5.06E-01	N/A	N/A	9.60E-01	3.88E-01	9.00E-01	N/A

Table S5. P-values for Dunn's test with the relative abundance of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Dunn's test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Conventional tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Conventional tillage - Biological based	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
No tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
No tillage - Biological based	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Reduced input - Biological based	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table S6. Summary of the p values from Spearman's rank correlation tests with gene relative abundance data. Values in bold indicate a significant difference ($p \leq 0.05$).

Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
<i>napA</i>		1.66E-07	4.74E-01	< 2.2e-16	1.43E-08	2.30E-06	8.67E-02	1.28E-08	4.26E-06
<i>narG</i>	1.66E-07		4.11E-02	2.74E-04	8.32E-03	3.30E-03	4.70E-01	3.12E-02	3.63E-01
<i>nifH</i>	4.74E-01	4.11E-02		9.83E-01	7.64E-02	7.37E-03	2.02E-01	8.42E-01	2.86E-01
<i>nirA</i>	< 2.2e-16	2.74E-04	9.83E-01		4.60E-02	5.80E-01	6.15E-01	1.08E-01	5.87E-01
<i>nirB</i>	1.43E-08	8.32E-03	7.64E-02	4.60E-02		8.05E-01	6.89E-01	5.47E-01	9.87E-01
<i>nirK</i>	2.30E-06	3.30E-03	7.37E-03	5.80E-01	8.05E-01		4.84E-03	1.98E-02	1.26E-02
<i>nirS</i>	8.67E-02	4.70E-01	2.02E-01	6.15E-01	6.89E-01	4.84E-03		2.12E-04	1.76E-03
<i>norB</i>	1.28E-08	3.12E-02	8.42E-01	1.08E-01	5.47E-01	1.98E-02	2.12E-04		7.65E-05
<i>nosZ</i>	4.26E-06	3.63E-01	2.86E-01	5.87E-01	9.87E-01	1.26E-02	1.76E-03	7.65E-05	

Table S7. Summary of Spearman's correlation coefficient (rho) for Spearman's rank correlation test with gene relative abundance data. Rho values in bold indicate a statistically significant correlation ($p \leq 0.05$), as shown above.

Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
<i>napA</i>		8.48E-01	1.54E-01	9.81E-01	8.80E-01	8.03E-01	3.57E-01	8.81E-01	7.91E-01
<i>narG</i>	8.48E-01		4.20E-01	6.78E-01	5.26E-01	5.75E-01	1.55E-01	4.41E-01	1.94E-01
<i>nifH</i>	1.54E-01	4.20E-01		-4.57E-03	3.69E-01	5.33E-01	2.70E-01	4.29E-02	2.27E-01
<i>nirA</i>	9.81E-01	6.78E-01	-4.57E-03		4.11E-01	1.19E-01	-1.08E-01	3.37E-01	1.17E-01
<i>nirB</i>	8.80E-01	5.26E-01	3.69E-01	4.11E-01		5.31E-02	-8.62E-02	1.29E-01	3.48E-03
<i>nirK</i>	8.03E-01	5.75E-01	5.33E-01	1.19E-01	5.31E-02		5.55E-01	4.72E-01	5.01E-01
<i>nirS</i>	3.57E-01	1.55E-01	2.70E-01	-1.08E-01	-8.62E-02	5.55E-01		6.87E-01	6.04E-01
<i>norB</i>	8.81E-01	4.41E-01	4.29E-02	3.37E-01	1.29E-01	4.72E-01	6.87E-01		7.19E-01
<i>nosZ</i>	7.91E-01	1.94E-01	2.27E-01	1.17E-01	3.48E-03	5.01E-01	6.04E-01	7.19E-01	

Table S8. P-values for statistical tests with the richness index Chao 1 of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Shapiro-Wilk test				Levene's test	One-way ANOVA	Kruskal-Wallis test
Null Hypothesis	The sample distribution is normal				$\sigma_1 = \sigma_2$	$\mu_1 = \mu_2$	Median ₁ = Median ₂
Soil groups	Conventional tillage	No tillage	Reduced input	Biological based			
<i>napA</i>	4.89E-01	6.42E-01	2.90E-01	2.63E-01	9.37E-01	3.56E-01	N/A
<i>narG</i>	4.66E-01	5.43E-01	2.78E-01	2.82E-01	9.42E-01	9.37E-01	N/A
<i>nifH</i>	9.76E-01	3.87E-03	6.53E-01	9.76E-01	7.80E-01	N/A	1.80E-02
<i>nirA</i>	5.72E-01	4.34E-01	4.55E-01	5.53E-01	9.60E-01	2.65E-01	N/A
<i>nirB</i>	4.85E-01	4.86E-01	3.71E-01	5.47E-01	9.99E-01	7.99E-01	N/A
<i>nirK</i>	2.50E-01	3.67E-02	7.66E-02	1.05E-03	9.88E-01	N/A	1.68E-02
<i>nirS</i>	8.12E-01	1.16E-01	3.55E-01	8.13E-01	6.72E-01	8.52E-04	N/A
<i>norB</i>	9.10E-01	2.92E-03	9.44E-01	5.08E-01	2.25E-01	N/A	2.35E-01
<i>nosZ</i>	7.47E-01	4.99E-01	8.99E-01	4.85E-01	5.12E-01	5.86E-01	N/A

Table S9. P-values for Tukey's HSD test with the richness index Chao 1 of counts of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Tukey's HSD test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	N/A	N/A	N/A	N/A	7.37E-04	N/A	N/A
Conventional tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	N/A	8.59E-03	N/A	N/A
Conventional tillage - Biological based	N/A	N/A	N/A	N/A	N/A	N/A	2.11E-01	N/A	N/A
No tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	N/A	7.05E-01	N/A	N/A
No tillage- Biological based	N/A	N/A	N/A	N/A	N/A	N/A	6.50E-02	N/A	N/A
Reduced input - Biological based	N/A	N/A	N/A	N/A	N/A	N/A	4.07E-01	N/A	N/A

Table S10. P-values for Dunn's test with the richness index Chao 1 of counts of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Dunn's test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	1.00E+00	N/A	N/A	1.00E+00	N/A	N/A	N/A
Conventional tillage - Reduced input	N/A	N/A	1.33E-01	N/A	N/A	2.91E-02	N/A	N/A	N/A
Conventional tillage - Biological based	N/A	N/A	1.00E+00	N/A	N/A	2.03E-01	N/A	N/A	N/A
No tillage - Reduced input	N/A	N/A	5.39E-02	N/A	N/A	1.65E-01	N/A	N/A	N/A
No tillage - Biological based	N/A	N/A	1.00E+00	N/A	N/A	7.85E-01	N/A	N/A	N/A
Reduced input - Biological based	N/A	N/A	3.30E-02	N/A	N/A	1.00E+00	N/A	N/A	N/A

Table S11. P-values for statistical tests with the richness index Chao 2 of counts of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Shapiro-Wilk test				Levene's test	One-way ANOVA	Kruskal-Wallis test
Null Hypothesis	The sample distribution is normal				$\sigma_1 = \sigma_2$	$\mu_1 = \mu_2$	Median ₁ = Median ₂
Soil groups	Conventional tillage	No tillage	Reduced input	Biological based			
<i>napA</i>	3.27E-01	4.60E-01	4.26E-01	2.38E-01	9.19E-01	4.17E-01	N/A
<i>narG</i>	2.88E-01	4.18E-01	2.19E-01	2.26E-01	9.91E-01	9.51E-01	N/A
<i>nifH</i>	7.54E-01	2.38E-01	1.62E-01	2.98E-01	5.93E-01	3.00E-01	N/A
<i>nirA</i>	3.24E-01	2.55E-01	4.23E-01	3.80E-01	9.32E-01	4.55E-01	N/A
<i>nirB</i>	2.55E-01	2.75E-01	2.57E-01	3.74E-01	9.98E-01	9.55E-01	N/A
<i>nirK</i>	5.32E-02	7.63E-03	8.64E-03	6.93E-03	9.95E-01	N/A	2.18E-01
<i>nirS</i>	3.70E-01	2.47E-01	2.80E-01	4.17E-01	9.87E-01	2.57E-01	N/A
<i>norB</i>	3.29E-01	6.27E-02	7.21E-01	1.90E-01	8.45E-01	4.62E-01	N/A
<i>nosZ</i>	2.30E-01	6.70E-01	7.22E-01	5.40E-01	6.34E-01	6.51E-01	N/A

Table S12. P-values for statistical tests with the Inverse Simpson values of the counts of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Shapiro-Wilk test				Levene's test	One-way ANOVA	Kruskal-Wallis test
Null Hypothesis	The sample distribution is normal				$\sigma_1 = \sigma_2$	$\mu_1 = \mu_2$	Median ₁ = Median ₂
Soil groups	Conventional tillage	No tillage	Reduced input	Biological based			
<i>napA</i>	4.73E-01	6.37E-03	5.07E-03	6.37E-03	3.63E-01	N/A	6.96E-05
<i>narG</i>	N/A	N/A	N/A	N/A	4.44E-05	N/A	N/A
<i>nifH</i>	1.27E-01	2.66E-01	2.08E-01	1.60E-01	2.00E-01	6.52E-01	N/A
<i>nirA</i>	9.00E-02	1.25E-01	1.70E-01	2.87E-02	6.90E-01	N/A	8.84E-04
<i>nirB</i>	1.49E-01	2.33E-01	9.44E-02	2.87E-02	6.16E-01	N/A	5.77E-04
<i>nirK</i>	6.00E-02	9.95E-02	1.81E-01	2.05E-01	4.85E-01	<2e-16	N/A
<i>nirS</i>	2.26E-01	7.08E-02	1.79E-01	1.15E-01	6.44E-01	1.57E-05	N/A
<i>norB</i>	2.15E-01	7.04E-02	1.06E-01	8.94E-02	3.11E-01	8.76E-15	N/A
<i>nosZ</i>	N/A	N/A	N/A	N/A	1.33E-04	N/A	N/A

Table S13. P-values for Tukey's HSD test with the Inverse Simpson values of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Tukey's HSD test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	N/A	N/A	N/A	0.00E+00	2.73E-03	0.00E+00	N/A
Conventional tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	0.00E+00	5.67E-02	5.00E-07	N/A
Conventional tillage - Biological based	N/A	N/A	N/A	N/A	N/A	0.00E+00	9.98E-01	2.62E-02	N/A
No tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	0.00E+00	6.40E-06	0.00E+00	N/A
No tillage- Biological based	N/A	N/A	N/A	N/A	N/A	0.00E+00	4.18E-03	0.00E+00	N/A
Reduced input - Biological based	N/A	N/A	N/A	N/A	N/A	3.45E-01	3.86E-02	3.18E-04	N/A

Table S14. P-values for Dunn's test with the Inverse Simpson values of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Dunn's test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	8.35E-01	N/A	N/A	1.00E+00	1.00E+00	N/A	N/A	N/A	N/A
Conventional tillage - Reduced input	1.86E-02	N/A	N/A	1.00E+00	4.31E-01	N/A	N/A	N/A	N/A
Conventional tillage - Biological based	5.49E-05	N/A	N/A	1.81E-01	1.12E-01	N/A	N/A	N/A	N/A
No tillage - Reduced input	8.35E-01	N/A	N/A	2.87E-02	9.14E-03	N/A	N/A	N/A	N/A
No tillage - Biological based	1.86E-02	N/A	N/A	6.14E-04	1.18E-03	N/A	N/A	N/A	N/A
Reduced input - Biological based	8.35E-01	N/A	N/A	5.15E-01	1.00E+00	N/A	N/A	N/A	N/A

Table S15. P-values for statistical tests with the Shannon diversity of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Shapiro-Wilk test				Levene's test	One-way ANOVA	Kruskal-Wallis test
Null Hypothesis	The sample distribution is normal				$\sigma_1 = \sigma_2$	$\mu_1 = \mu_2$	Median ₁ = Median ₂
Soil groups	Conventional tillage	No tillage	Reduced input	Biological based			
<i>napA</i>	3.28E-02	3.17E-02	2.50E-01	3.28E-02	2.09E-01	N/A	2.03E-04
<i>narG</i>	2.47E-02	1.55E-02	9.26E-01	6.07E-01	1.38E-01	N/A	1.90E-04
<i>nifH</i>	2.08E-01	2.63E-01	3.25E-01	3.08E-01	6.31E-01	8.35E-01	N/A
<i>nirA</i>	9.44E-02	6.95E-02	2.21E-01	1.31E-01	9.65E-01	3.55E-03	N/A
<i>nirB</i>	5.13E-02	5.13E-02	6.92E-02	2.07E-01	9.59E-01	5.85E-02	N/A
<i>nirK</i>	7.78E-02	5.51E-02	3.29E-02	9.11E-02	9.24E-01	N/A	1.77E-04
<i>nirS</i>	1.88E-01	1.35E-01	1.73E-01	1.52E-01	8.03E-01	2.76E-03	N/A
<i>norB</i>	1.61E-01	1.55E-02	7.96E-02	1.01E-02	9.52E-01	N/A	1.44E-03
<i>nosZ</i>	7.63E-01	5.08E-02	1.61E-01	7.03E-02	8.11E-01	<2E-16	N/A

Table S16. P-values for Tukey’s HSD test with the Shannon diversity of genes associated with nitrogen metabolism copies. “N/A” indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Tukey's HSD test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	N/A	N/A	N/A	N/A	N/A	0.00E+00	2.73E-03	0.00E+00	N/A
Conventional tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	0.00E+00	5.67E-02	5.00E-07	N/A
Conventional tillage - Biological based	N/A	N/A	N/A	N/A	N/A	0.00E+00	9.98E-01	2.62E-02	N/A
No tillage - Reduced input	N/A	N/A	N/A	N/A	N/A	0.00E+00	6.40E-06	0.00E+00	N/A
No tillage- Biological based	N/A	N/A	N/A	N/A	N/A	0.00E+00	4.18E-03	0.00E+00	N/A
Reduced input - Biological based	N/A	N/A	N/A	N/A	N/A	3.45E-01	3.86E-02	3.18E-04	N/A

Table S17. P-values for Dunn's test with the Shannon diversity of genes associated with nitrogen metabolism copies. "N/A" indicates the test was not appropriate and p-values in bold indicate a significant difference ($p \leq 0.05$).

Test	Dunn's test								
Null Hypothesis	$\mu_1 = \mu_2$								
Genes	<i>napA</i>	<i>narG</i>	<i>nifH</i>	<i>nirA</i>	<i>nirB</i>	<i>nirK</i>	<i>nirS</i>	<i>norB</i>	<i>nosZ</i>
Conventional tillage - No tillage	1.00E+00	1.00E+00	N/A	N/A	N/A	4.88E-05	N/A	0.00E+00	N/A
Conventional tillage - Reduced input	1.37E-02	1.75E-01	N/A	N/A	N/A	1.63E-01	N/A	5.00E-07	N/A
Conventional tillage - Biological based	1.77E-04	1.42E-01	N/A	N/A	N/A	1.46E-01	N/A	2.62E-02	N/A
No tillage - Reduced input	9.11E-01	1.42E-01	N/A	N/A	N/A	1.46E-01	N/A	0.00E+00	N/A
No tillage - Biological based	6.29E-02	1.75E-01	N/A	N/A	N/A	1.63E-01	N/A	0.00E+00	N/A
Reduced input - Biological based	6.35E-01	5.27E-05	N/A	N/A	N/A	1.00E+00	N/A	3.18E-04	N/A

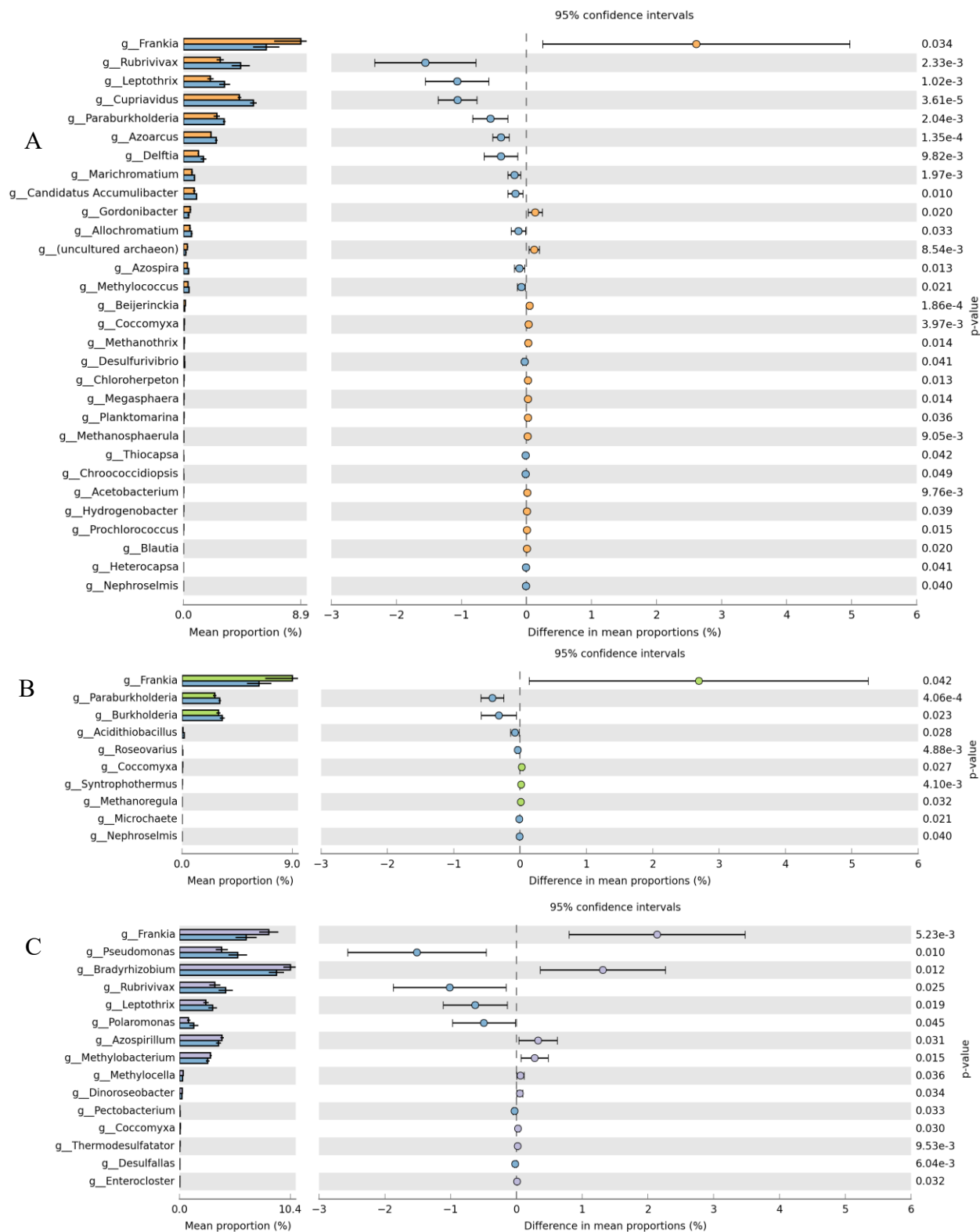


Figure S1. Genera with *nifH* genes significantly different between conventional tillage soil (in blue) and the other soils from the assembled contigs. Those enriched in no tillage soil compared to conventional tillage soil are shown in yellow (A), those enriched in reduced input soil compared to conventional tillage soil are shown in green (B) and those enriched in biologically based soil compared to conventional tillage soil are shown in purple (C). The data (generated in Megan, six metagenomes for each soil) were analyzed using STAMP with the two group analysis option (each soil compared to conventional tillage soil) and Welch's two sided t-test ($p < 0.05$).

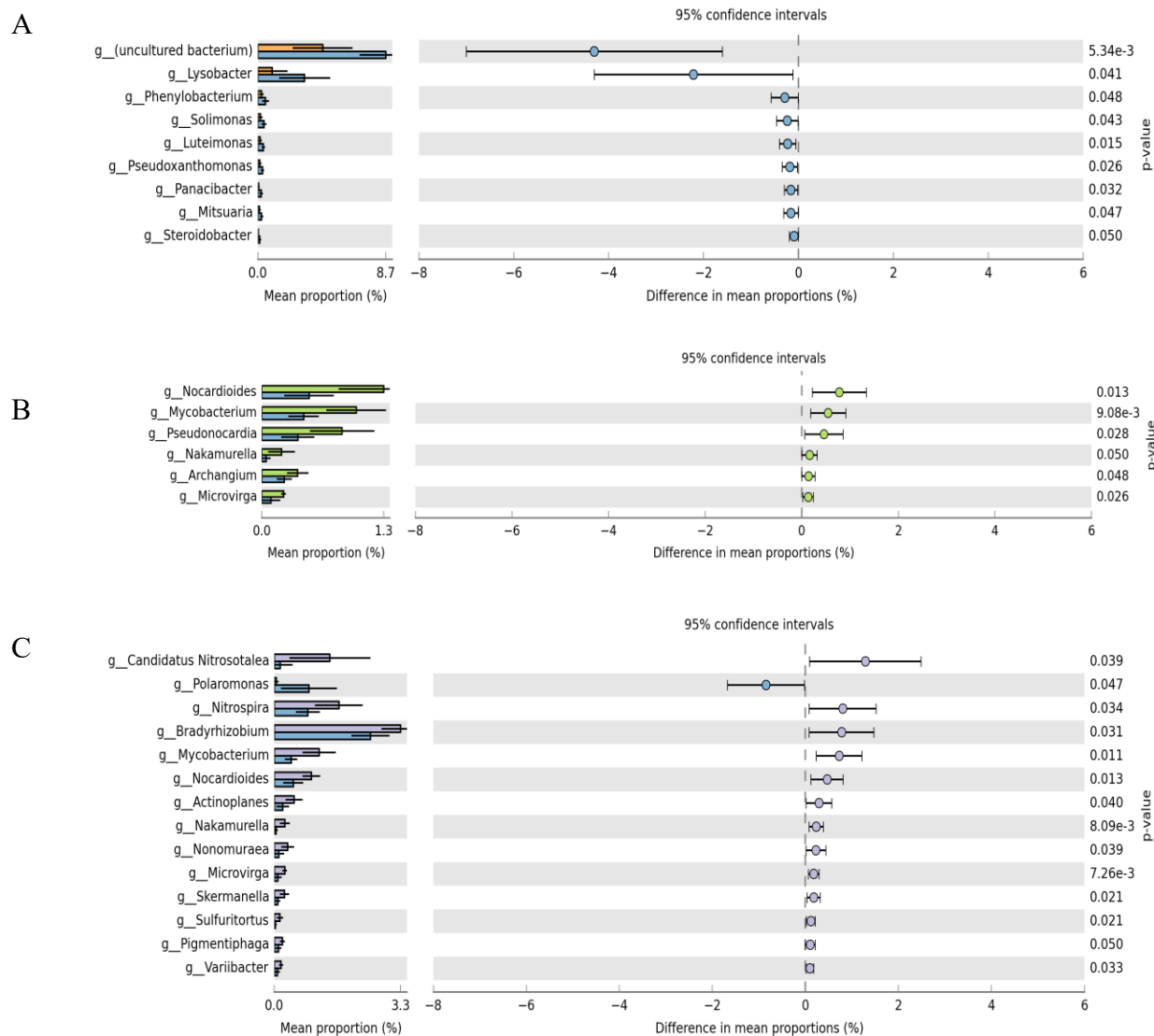


Figure S2. Genera significantly different between conventional tillage (in blue) and the other three soils from the assembled contigs. Those enriched in soil 1 compared to no tillage soil are shown in blue (no genera were enriched in no tillage soil compared to conventional tillage soil) (A), those enriched in reduced input soil compared to conventional tillage soil are shown in green (B) and those enriched in biologically based soil compared to conventional tillage soil are shown in purple (C). The data (generated in Megan, six metagenomes for each soil) were analyzed using STAMP with the two group analysis option (each soil compared to conventional tillage soil) and Welch's two sided t-test ($p < 0.05$).