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Exploring the Relationships between Greenhouse Gas Emissions, Yields, and Soil Properties in Cropping Systems

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Abstract: Relationships between greenhouse gas emissions, yields, and soil properties are not well known. Utilizing two datasets from long-term cropping systems in Illinois, USA, our we aim to address these knowledge gaps. The objective of this study was to explore the relationships between the physical and chemical properties and greenhouse gas (GHG) emissions of soil, and cash crop yields over a four-year time-period and following 15 years of treatment implementation in Illinois, USA. The experimental layout was a split-plot arrangement involving rotation and tillage treatments in a randomized complete block design with four replications. The studied crop rotations were continuous corn [*Zea mays* L.] (CCC), corn-soybean [*Glycine max* (L.) Merr.] (CS), continuous soybean (SSS), and corn-soybean-wheat [*Triticum aestivum* L.] (CSW), with each phase being present for every year. The tillage options were chisel tillage (T) and no-tillage (NT). We used an array of multivariate approaches to analyze both of our datasets that included 31 soil properties, GHG emissions (N_2O, CO_2, and CH_4) and cash crop yields. The results from our analyses indicate that N_2O emissions are associated with a low soil pH, an increased Al concentration, the presence of soil nitrate throughout the growing season, an increase in plant available water (PAW) and an increased soil C concentration. Likewise, soil CO_2 respiration was correlated with low pH, elevated Al concentrations, low Ca, increased PAW, higher levels of microbial biomass carbon (MBC), and lower water aggregate stability (WAS). Emissions of CH_4 were associated with increased levels of MBC. Lastly, the yield index (YdI) was correlated with lower levels of soil Ca and available P and lower values of WAS. The association between high YdI and lower WAS can be attributed to tillage, as tillage lowers WAS, but increases yields in highly productive cropping systems in the Midwest.

Keywords: rotations; tillage; nitrous oxide; carbon dioxide; methane; soil properties; corn; soybean; wheat; Midwest agriculture

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1. Introduction

The Midwestern United States (US) is regarded as having some of the most productive lands in the world; deep and dark Mollisols cover over half of the state of Illinois [1]. Accordingly, Illinois places in the top two states for corn (*Zea mays* L.) and soybean [*Glycine max* (L). Merr.] production, with nearly 5 million ha of corn planted and 4 million ha of soybean planted each year [2]. Due to a large amount of production expected to feed a growing global population, significant inputs of N and P are added each year in order to achieve maximum productivity. Specifically, in 2016, 954,400 tons of N and 446,350 tons of P were applied to 98% and 86% of the planted corn area, respectively [2]. This demand for high yield does not come without consequences; agriculture contributes around 9% of total US greenhouse gas (GHG) emissions. Of this 9%, carbon dioxide (CO_2) makes up the majority

(81%), followed by methane (CH_4) (11%) and then nitrous oxide (N_2O) (6%) [3]. In addition to gaseous losses, agricultural land is deteriorated each year due to erosion, flooding, mining, urban development, and other sensitive agricultural practices; these destructive consequences lead to soil contamination and have an overall undesirable effect on the soil quality [4]. Therefore, the protection of fertile soil is critical to human welfare [5].

Soil management is critical both for productivity and to limit environmental degradation. Agricultural soil management includes fertilizer use, agrochemicals, tillage practices, and crop rotation systems. These management decisions influence agricultural N_2O emissions which constitute approximately 80% of the total annual N_2O emissions in the US [3]. The global warming potentials (GWP) of N_2O and CH_4 are 298 and 25 times greater than that of CO_2, respectively. Global warming potential is a measure of the amount of energy that one kilogram of a certain GHG will absorb over a given time period, usually 100 years, relative to CO_2 [3]. Nitrous oxide emissions are affected by the N application rate, fertilizer source, application technique and timing, use of other chemicals, irrigation, crop type, and residual N and C from previous crops and fertilizers [6–8]. Nitrogen added to the system through fertilizers, other agrochemicals, or residue decomposition stimulates N_2O production by providing a substrate for microbial N conversion through nitrification and denitrification [9,10]. Nitrification occurs when ammonium is added to the soil through either fertilizers, N fixation by legumes, or mineralized soil organic matter (SOM) [11]. Microbial transformations cause the ammonium to be converted to nitrite and eventually to nitrate, though small quantities can be lost as N_2O [12]. Similarly, low soil oxygen conditions lead to microbial denitrification as denitrifiers use nitrate as a terminal electron acceptor, and N_2O is an intermediate step in complete denitrification to N_2 gas [11,13,14]. Throughout the US Corn Belt (Illinois, Iowa, Indiana, Ohio, Southern and Western Minnesota, and Eastern Nebraska), spring fertilization application is common. However, events involving saturating rain to flooding routinely occur during this time as well, so water-logging of the soil ensues, which promotes large denitrification events due to low soil oxygen concentrations, wherein a large proportion of annual N_2O flux can occur over a short time scale, ranging from hours to weeks [15].

The fertilization of crops is inherently leaky; many take up less than 50% of the N applied, leaving the N that is not stored in the soil subject to loss [16]. Due to the excess N in the system and the connection between this N and GHG emissions, the US Corn Belt tends to be a major source of agricultural GHG emissions [3]. Greater N_2O emissions have been reported in continuous corn operations compared to corn in rotation, due to increased fertilizer input which is common in continuous corn operations. In addition, continuous corn operations return greater amounts of residue to the soil compared to rotated corn and this increased amount of C substrate allows for greater microbial decomposition and increased denitrification [12,17–19]. However tillage studies have been less conclusive; no-till (NT) or reduced till can have less, more, or no effect on N_2O emissions compared to conventional tillage systems (T) [9,12,20]. Two common agricultural practices aimed at improving soil properties are crop rotations and no-tillage systems. These management practices directly influence the soil organic carbon (SOC) content by affecting the quantity, quality, and rate of crop residue decomposition returned to the system; SOC is an indicator of soil health and quality [21,22]. The benefits of SOC are an increase in nutrient availability, an increased cation exchange capacity (CEC), an improved water holding capacity, and a lowered bulk density [21,22].

Despite the benefits to SOC under no-till systems, corn yields in the Midwest tend to be greater when a tillage regime is used compared to a no-till regime [17,23–25]. In a recent study conducted by Daigh, et al. [26] at several sites in the Midwest, yield increases due to tillage were correlated with the crop phase of the rotation, especially during non-drought conditions. Greater decreases in yield with long-term (5+ years) NT in corn systems were observed in a global meta-analysis conducted by Pittelkow, et al. [27]; the reduced yield with NT systems has been attributed to waterlogging, poor establishment, compaction, and nutrient deficiencies [24,28,29].

Just as tillage has been shown to increase yields in the Midwest, crop rotation has been well documented to increase yields in both corn and soybean years [17,26,30–36]. However, some soil properties, such as SOC, have been shown to increase with more years of growing corn due to the larger residue return from corn back to the soil system [21,23,37–40]. The increases in SOC can also be related to increased levels of N and P [41,42]. The intricate interactions of crop rotations influence the soil environment through the quantity and quality of residue decomposition. Crop rotation decreases weed and insect pest pressure and also increases the residue quality by improving the retention of N in microbial biomass [43]. The inclusion of crops with high C/N ratios in their residue, like corn and wheat (*Triticum aestivum* L.), combined with NT has been found to increase SOC, TN, and aggregate stability [44,45].

In Behnke, et al. [19], a study published previously using some of the data that is presented subsequently in the current study, it was found that tillage increased the yields of corn and soybean. Likewise, utilizing a corn-soybean rotation (CS) increased corn yields by 20% while reducing N_2O emissions by nearly 35%; soybean yields were 7% greater with no reduction in N_2O emissions. The authors found that a CS rotation can increase yields and reduce GHG emissions compared to continuous corn or continuous soybean systems alone. Furthermore, moving to a corn-soybean-wheat rotation did not further increase yields or reduce N_2O emissions. This study highlights how management decisions can affect soil GHG emissions and crop production. As a result, the interactions between several soil properties, GHG emissions and yields need to be further evaluated. Several studies have included soil properties related to tillage and crop rotation practices, but few have taken into account GHG emissions; even fewer have been conducted on a long-term scale (15+ years). In order to understand the dynamic relationships between these variables, a multivariate statistical analysis on a large dataset is urgently needed. Thus, our goal for this project was to elucidate the relationships between GHG emissions, soil properties, and crop yields in typical cropping systems in Illinois.

2. Materials and Methods

2.1. Site Characterization and Experimental Layout

This study was established in 1996 at the Northwestern Illinois Agricultural Research and Demonstration Center (40°55′50″ N, 90°43′38″ W), approximately 8 km northwest of Monmouth, IL. The mean annual precipitation in this area is approximately 978 mm and the mean annual temperature is 16 °C [46]. Soils at the experimental site were predominantly comprised of Sable silty clay loam (fine-silty, mixed, mesic Typic Endoaquoll) and Muscatune silt loam (fine-silty, mixed, mesic Aquic Argiudoll). In addition, the plots contained a small area of Osco silt loam (fine-silty, mixed, mesic Typic Argiudoll) [47]. The plot layout consisted of a split-plot arrangement of four rotation levels and two tillage levels in a randomized complete block design with four replications. Crop rotations of continuous corn (CCC), corn-soybean (CS), corn-soybean-wheat (CSW), soybean-corn (SC), soybean-wheat-corn (SWC), continuous soybean (SSS), and wheat-corn-soybean (WCS) were assigned to the main plots, with each phase of each rotation (a total of seven main plots) being present during each year. The two subplot treatments were tillage (T) and no-till (NT). The main plots were 22 m long by 12 m wide, with subplots being 22 m long by 6 m wide. It is important to note that we did not sample the NT pair for the CSW rotation, nor the soybean phase of the CSW rotation (SWC) for greenhouse gas (GHG) emissions; however, soil samples and yields were taken in those plots. The first letter of the cropping system abbreviation indicates the crop for which a property is being reported. The cropping systems used in the analysis included no-till continuous corn (CCC-NT); tilled continuous corn (CCC-T); no-till corn of the corn-soybean rotation (CS-NT); tilled corn of the corn-soybean rotation (CS-T); no-till corn of the corn-soybean-wheat rotation (CSW-NT); tilled corn of the corn-soybean-wheat rotation (CSW-T); no-till soybean of the soybean-corn rotation (SC-NT); tilled soybean of the soybean-corn rotation (SC-T); tilled soybean-wheat-corn

(SWC-T); no-till soybean-wheat-corn (SWC-NT); no-till continuous soybean (SSS-NT); tilled continuous soybean (SSS-T); no-till wheat of the wheat-corn-soybean rotation (WCS-NT); and tilled wheat of the wheat-corn-soybean rotation (WCS-T).

Following fall harvest, the tilled corn and soybean plots were cultivated using a disk ripper operated at a depth of about 35 cm. In the spring, a soil finisher was used to prepare the seedbed in tilled plots. Wheat plots were tilled using a rototiller in the fall before planting. No-till plots received zero tillage. Fertilizer and pest management decisions were made using best management practices according to the Illinois Agronomy Handbook [48]. Application of N fertilizer to both tilled and no-till corn was done in the spring, at or before the time of planting, as injected incorporated urea ammonium nitrate (UAN), at rates of 246 kg-N ha^{-1} for CCC and 202 kg-N ha^{-1} for CS and CSW. The increased fertilization rate for CCC compared to rotated corn was implemented following the Illinois Agronomy Handbook recommendations for the area [48]. The wheat phase of the cropping rotation received 34 kg-N ha^{-1} at planting and 56 kg-N ha^{-1} as a spring topdress of UAN. No N fertilizer was applied to soybean treatments. Additional P and K fertilizer were applied in the fall every two years, based on soil test results. Corn plots were planted in April or May in 76-cm rows at a seeding rate of 86,500 ha^{-1}. Soybean plots were planted in May in 38-cm rows at a seeding rate of approximately 358,000 ha^{-1}. Wheat plots were planted in late September or early October, with seeds drilled in 19-cm rows at a rate of about 3.7×10^6 seeds ha^{-1}. Due to winter wheat damage during the winter of 2013–14, wheat was replaced by oats [*Avena sativa* L.] planted on 14 April 2014. Oat yields were similar to wheat yields found in other years, and for the purpose of this report, we will treat the 2014 oat crop as wheat. Yields were harvested using a plot combine (Almaco, Nevada, IA, USA) and adjusted to 15.5%, 13%, and 13.5% moisture levels for corn, soybean, and wheat, respectively. Detailed information, including dates, is summarized in Appendix A (Appendix A Table A1).

2.2. Gas Sampling Procedures

Soil GHG emissions were taken weekly over a period of 4 growing seasons (2012–2015) following the GRACEnet chamber-based trace gas flux measurement protocol [49]. Beginning in March 2012, 0.031 m^2 polyvinyl chloride (PVC) white chamber bases were installed in the experimental plots immediately after planting and initial fertilizer application. Two chamber bases were used in corn plots: one in-row and one between-row. One chamber was used for each of the soybean and wheat plots. Soil CO_2 emissions were used to represent soil respiration. Due to severe weather, we were not able to collect wheat data in 2014. The chamber tops were also made of white PVC, and contained a vent tube, sampling septa, and insulation foam to create an airtight seal to the chamber bases. The chamber bases were left in the field for the growing season and were removed before harvest.

Soil GHG measurements were conducted near noon when air temperatures were around the average for the day. Gas samples were taken by placing the chamber top on the base and extracting 15 mL using a Precision-Glide® needle syringe at 0, 10, 20, and 30 min. Gas samples were then transferred into 10 mL aluminum crimp top vials with 20 mm Pharma-Fix Butyl® septa. Gas samples were analyzed on a gas chromatograph with an electron capture detector and flame ionization detector (Shimadzu® GC 2014 with AOC-5000). Soil GHG fluxes were calculated as the rate of change in gas concentration inside the chamber headspace over the 30 min collection period. The number of sampling events by year is included in Appendix A (Table A2).

2.3. Soil Sampling and Analyses

Two soil cores (0–10 cm depth) were collected from each plot and each sampling event during gas sampling for the 2013–2015 growing seasons (complete list found in Appendix A Table A2), composited, and then analyzed for available N concentrations in ammonium and nitrate (NH_4–N and NO_3–N). Concentrations of NH_4–N and NO_3–N from soil extracts (1 M KCl) were measured colorimetrically by flow injection analysis with a Lachat Quick-Chem 8000 (Lachat Quickchem Analyzer, Lachat Instruments Loveland, CO, USA). The concentrations of NH_4–N and NO_3–N were used to calculate the soil nitrogen intensity throughout the growing season, following the protocol in Venterea, et al. [8]; this will be discussed later. In addition, to evaluate long-term treatment effects on soil properties, three soil cores, 4.3 cm in diameter, were taken in May of 2014 for each subplot to a depth of 20 cm with a tractor-mounted hydraulic probe (Amity Technology, Fargo, ND, USA). Soil cores were cut to 0–10 and 10–20 cm depths and stored refrigerated at 4 °C in plastic bags until analysis. Soil samples from depths of 0–10 and 10–20 cm were combined in this study. Soil samples were air-dried, ground, and sieved through a 2-mm sieve, and the three subsamples from each plot were composited to provide one sample per plot for the remainder of the soil analyses. The soil physical properties measured included soil texture (% sand, % silt, and % clay) by the hydrometer method [50]; soil moisture (Ho, %) at each NO_3 and NH_4 soil sampling event (determined gravimetrically) [51]; permanent wilting points (PWP, $cm^3\ cm^{-3}$) (determined from separate soil cores, 4.8 cm in diameter), and plant available water (PAW, $cm^3\ cm^{-3}$) (measured using a Decagon WP4C device (Decagon Devices, Inc., Pullman, WA, USA) following Basche, et al. [52]). Likewise, soil bulk density (Bd, $g\ cm^{-3}$) was determined for each subsample using the core method [53]. Lastly, three subsamples from the 1–2-mm soil fraction were used to determine the water aggregate stability (WAS) with an Eijkelkamp wet sieving apparatus (Eijkelkamp Agrisearch Equipment, Giesbeek, The Netherlands), following Kemper and Rosenau [54]. The microbial biomasses of C (MBC, $\mu g\ g^{-1}$) and N (MBN, $\mu g\ g^{-1}$) were analyzed on a Shimadzu TOC-L and TNM-L analyzer (Shimadzu Corporation, Kyoto, Japan), following the modified chloroform fumigation extraction protocol for air-dried soils described in Zuber, et al. [55]. Furthermore, soil macronutrients included soil ammonia intensity (NH_4, mg-N $kg^{-1}day^{-1}$ during the growing season), soil nitrate intensity (NO_3, mg-N $kg^{-1}day^{-1}$ during the growing season), and total soil nitrogen intensity (TIN, mg-N $kg^{-1}day^{-1}$ during the growing season), which was determined by trapezoidal integration of soil concentration over time [8]—NH_4 and NO_3 separately and the sum of the two for TIN.

Air-dried soil samples were sent to a commercial laboratory for the determination of pH, CEC, SOM, C, N, C/N, Pa, K, S, Ca, Mg, Na, B, Fe, Mn, Cu, Zn, and Al (Brookside Laboratories, Inc., New Bremen, OH, USA). Soil pH was analyzed using potentiometry (1:1 water and soil ratio) [56]; cation exchange capacity (CEC, cmol kg^{-1}) was determined by the summation method of exchangeable cations (Ca, Mg, K, Na, H) (Sumner and Miller, 1996). The quantities of soil organic matter (SOM, %), carbon (C, %), nitrogen (N, %), and the carbon/nitrogen ratio (C/N) were analyzed using dry combustion [57,58]. Available phosphorus (Pa, mg kg^{-1}) was measured through Bray I extraction [59] while potassium (K, mg kg^{-1}), sulfur (S, mg kg^{-1}), calcium (Ca, mg kg^{-1}), magnesium (Mg, mg kg^{-1}), sodium (Na, mg kg^{-1}), boron (B, mg kg^{-1}), iron (Fe, mg kg^{-1}), manganese (Mn, mg kg^{-1}), copper (Cu, mg kg^{-1}), zinc (Zn, mg kg^{-1}), and aluminum (Al, mg kg^{-1}) concentrations were determined following Mehlich III extraction [60] and further analysis was conducted by inductively coupled plasma (ICP).

2.4. Data Analysis

The experiment aimed to test the relationships between GHG emissions, soil properties, and crop yields following the effects of cropping rotation and tillage that have occurred since 1996. Cumulative GHG emissions (N_2O, CO_2, and CH_4) were linearly extrapolated to predict fluxes for the growing season. The exact number of sampling events is included in the Appendix A (Table A2). A detailed description of the cumulative GHG calculations and other information is included in a previous publication [17]. Yields were standardized by crop to account for differences in yield levels, and values were normalized to a mean of 0 and standard deviation of 1. Therefore, the variable yield index (YdI) is unitless. The number of observations included in the original dataset before averaging by plot is included in the Appendix A (Table A3). The inclusion of both tables (Appendix A Tables A1 and A2) shows which variables were present throughout the growing season and which variables we sampled in the spring of 2014.

Two subsets of the data, analyzing GHG and YdI, were created to extract maximum information knowing that our software of preference to conduct multivariate analyses automatically removes observations with missing data (SAS 9.4, SAS Institute Inc., Cary, NC, USA, 2012). Thus, the first data set for GHG emissions included all 32 variables (including YdI), rendering a total of 32 observations with no missing data. A second data set for GHG emissions was comprised of 56 observations on 23 measured variables, excluding sand, silt, clay, Ho, PWP, PAW, NH_4, NO_3, and TIN. Similarly, the first data set for YdI included all 34 variables (including GHG emissions) rendering a total of 32 observations with no missing data. A second data set for YdI was comprised of 52 observations on 25 measured variables, excluding sand, silt, clay, Ho, PWP, PAW, NH_4, NO_3, and TIN.

The GHG, YdI, and soil variables measured had contrasting variances and units of measurement. The means and standard errors of the mean values for each variable were determined using the means procedure in SAS software (SAS 9.4, SAS Institute Inc., Cary, NC, USA). The mean and standard error values for each crop rotation, tillage, and crop rotation by tillage combination are included in the Appendix A (Tables A4–A8). To avoid having the variable with the highest variance dominate the results, all multivariate analyses were conducted on standardized data (mean = 0, standard deviation = 1) obtained with the STANDARD procedure in SAS. Pearson's correlation coefficients were calculated using the CORR procedure in SAS to explore correlations between GHG, YdI, and soil variables (Appendix A Table A9). Correlations between variable pairs were found to be $\geq |0.25|$ (moderate to high range) which, in most cases, indicated the need to deploy a data reduction technique such as principal component analysis (PCA) to avoid problems of multicollinearity by compiling the information into a new smaller set of uncorrelated variables. We performed a PCA using the PRINCOMP procedure in SAS. PCA creates new uncorrelated, orthogonal variables called principal components (PCs) that are linear combinations of the original raw variables that maximize the variability explained by the set of variables [61]. The PCA of the available variables in the data set determines coefficients in a new linear design [62]. The PCA technique uses the relationships between the original variables to develop a smaller set of components that empirically summarizes the correlations between the variables [63]. The new reduced set of variables or PCs contains almost as much information as the original variables but reveals relationships that would not typically result. Eigenvalues represent a special set of scalars associated with a linear system of equations; eigenvalues are comprised of all the variables tested and each explains a percentage of the variability [61] The reorganized and uncorrelated PCs contain loading factors or eigenvectors based on the contribution of variability and correlation to the PC axis [62]. We extracted PC scores with eigenvalues ≥ 1 that explained an important proportion of the total variability of each data set; these new variables are hereby called PC1 to PC8. Eight PCs were extracted from the first GHG dataset and seven PCs from the second GHG data set, as previously described. Eight PCs were extracted from both of the YdI data sets, as previously described. The PCA thus reduced the dimensionality of the first GHG dataset from 32 (correlated) variables to eight (uncorrelated) PCs (PC1 to PC8), and from 23 variables to seven uncorrelated linear combinations (PC1 to PC7) with limited loss of information in both data sets. Likewise, the PCA reduced the dimensionality of the first YdI dataset from 34 (correlated) variables to eight (uncorrelated) PCs (PC1 to PC8); and from 25 variables to eight uncorrelated linear combinations (PC1 to PC8), again with limited loss of information in both data sets. Soil, GHG, and YdI variable loadings $\geq |0.25|$ were considered in the interpretation of each set of PCs. Next, we fitted multiple linear regression models to the PCs extracted in each case using PROC REG in SAS to evaluate the relationships between soil, GHG, and YdI. Regression analyses were conducted using stepwise selection with sle = 0.1 and sls = 0.15.

3. Results

3.1. Greenhouse Gas 32 Variable Dataset

The PCA of the 32 variable dataset for GHG emissions rendered a set of eight uncorrelated variables or PCs (PC1 to PC8, Table 1) with eigenvalues larger than 1, which, when added together explained about 83% of the total variability contained in the GHG database. These eight PCs incorporated the 32 original variables but contained high loading factors based on their contributions to variability and correlations with the PC. PC1 had the largest eigenvalue (8.17) and explained around 26% of the variability with its eigenvector that included high positive loadings (>0.25) for CEC, N, and Fe. In addition, PC1 included high negative loadings (<−0.25) for pH, C/N, and B. PC2 had an eigenvalue of 6.66 and explained around 20% of the variability in the 32 variable set for GHG emissions. The eigenvector for PC2 had positive loadings for PWP, C, Ca, and Cu. The eigenvalue for PC3 was 3.28 and explained an additional 11% of the total variability. The eigenvector for PC3 included positive loadings for silt and SOM. Likewise, the eigenvector for PC3 contained negative loadings for clay, NH_4, NO_3, and TIN. The eigenvalue for PC4 was 2.41 and accounted for 8% of the variability. PC4 contained positive loadings for PAW, Pa, Mn, and Zn. In addition, PC4 contained negative loadings for sand and WAS. PC5 had an eigenvalue of 2.37 and explained 7% of the variability. PC5 included positive loadings for clay, MBN, and Na. Conversely, PC5 contained negative loadings for silt, Bd, and Mn. PC6 had an eigenvalue of 1.42 and explained 4% of the variability. The eigenvector for PC6 showed positive loadings for YdI, sand and MBC, and negative loadings for WAS and Na. The eigenvalue for PC7 was 1.31 and explained an additional 4% of the variability. The eigenvector for PC7 contained positive loadings for Bd, MBN, Na, and Zn. PC7 also contained a negative loading for CEC. The final PC8 had an eigenvalue of 1.07 and explained 3% of the variability, while its eigenvector showed positive loadings for PAW, Bd, and C, and a negative loading for Pa. These eight significant PCs were used as independent variables in our multiple regression analysis.

Table 1. Principal component analysis based on 32 observations modeling greenhouse gas (GHG) emissions (N_2O, CO_2, and CH_4) with 32 variables, with eigenvalues and the cumulative proportion of the dataset variability explained by eight principal components (PC) extracted from eigenvalues >1. Component correlation scores (eigenvalues) with loadings greater than |0.25| are in bold.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	8.17	6.66	3.28	2.41	2.37	1.42	1.31	1.07
Cum. Proportion	0.26	0.46	0.57	0.64	0.72	0.76	0.80	0.83
Soil Variable	**Component Correlation Scores**							
Yield Index (YdI)	−0.13	−0.16	0.13	0.11	0.19	**0.38**	−0.05	0.11
Sand	0.21	0.00	−0.01	**−0.26**	0.13	**0.33**	0.10	0.08
Silt	−0.09	−0.18	**0.30**	0.07	**−0.32**	−0.08	0.04	0.01
Clay	0.06	0.19	**−0.31**	−0.02	**0.30**	0.02	−0.06	−0.03
Ho	0.04	0.22	0.20	−0.18	−0.15	−0.10	−0.17	0.08
Permanent Wilting Points (PWP)	−0.08	**0.30**	0.10	−0.20	−0.04	−0.23	−0.09	−0.10
Plant Available Water (PAW)	0.10	−0.09	−0.06	**0.43**	0.02	0.06	−0.20	**0.44**
Soil Bulk Density (BD)	0.07	−0.03	0.06	−0.15	**−0.26**	−0.12	**0.60**	**0.25**
Water Aggregate Stability (WAS)	0.04	0.19	0.04	**−0.30**	0.03	**−0.38**	−0.05	0.08
pH	**−0.32**	−0.02	−0.13	−0.06	−0.09	−0.03	0.08	0.06
Cation Exchange Capacity (CEC)	**0.29**	0.11	0.13	0.06	0.04	−0.03	**−0.26**	−0.05
Soil Organic Matter (SOM)	0.23	0.18	**0.26**	0.01	0.07	0.11	0.05	0.20
C	0.13	**0.27**	0.25	0.05	0.03	0.12	0.03	**0.30**
N	**0.26**	0.18	0.18	−0.02	−0.05	0.09	0.07	0.16
C/N	**−0.26**	0.17	0.09	0.07	0.15	0.07	−0.09	0.18
Microbial Biomass Carbon (MBC)	−0.13	0.12	0.17	−0.02	−0.12	**0.45**	0.12	−0.12
Microbial Biomass Nitrogen (MBN)	−0.17	0.04	−0.03	−0.01	**0.40**	0.08	**0.37**	−0.22
NH_4	0.18	0.14	**−0.31**	−0.04	−0.15	0.11	0.08	−0.08
NO_3	0.19	0.11	**−0.37**	0.08	−0.07	0.09	0.02	0.08
Total Soil Nitrogen Intensity (TIN)	0.20	0.13	**−0.37**	0.03	−0.11	0.11	0.05	0.02
Pa	0.00	0.19	0.11	**0.39**	−0.07	0.00	−0.01	**−0.38**

Table 1. *Cont.*

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
K	0.23	0.05	−0.15	−0.03	−0.18	0.05	0.17	−0.12
S	0.25	−0.23	0.01	0.10	0.05	−0.10	0.03	0.08
Ca	0.01	**0.32**	−0.02	0.07	0.03	−0.03	0.13	0.05
Mg	−0.21	0.25	−0.16	0.04	−0.04	−0.05	−0.08	0.13
Na	0.05	−0.15	0.00	0.21	**0.31**	**−0.38**	**0.32**	0.23
B	**−0.27**	0.10	−0.13	0.13	0.05	−0.03	0.14	0.22
Fe	**0.25**	0.08	0.11	0.19	0.24	−0.12	0.04	−0.21
Mn	0.00	−0.09	−0.11	**0.32**	**−0.42**	−0.09	−0.05	−0.01
Cu	−0.11	**0.30**	−0.04	0.24	0.04	−0.17	−0.05	−0.02
Zn	0.00	0.19	0.18	**0.31**	−0.08	0.03	**0.34**	−0.23
Al	0.23	−0.23	0.08	−0.01	0.15	−0.14	−0.01	−0.20

3.2. Greenhouse Gas 23 Variable Dataset

The PCA of the 23 variable dataset for GHG emissions rendered a set of seven uncorrelated variables or PCs (PC1 to PC7, Table 2) with eigenvalues larger than 1, which, when added together explained about 80% of the total variability contained in the GHG database. These seven PCs incorporated the 23 original variables but contained high loading factors based on their contributions to variability and correlations with the PC. PC1 had the largest eigenvalue (6.04) and explained around 26% of the variability with its eigenvector that included high positive loadings (>0.25) for pH C/N, Mg, and B. In addition, PC1 included high negative loadings (<−0.25) for S and Al, C/N, and B. PC2 had an eigenvalue of 5.01 and explained around 22% of the variability in the 23 variable set for GHG emissions. The eigenvector for PC2 had positive loadings for CEC, SOM, C, N, Ca, and Zn. The eigenvalue for PC3 was 2.17 and explained an additional 10% of the total variability. The eigenvector for PC3 included positive loadings for YdI and MBN. Likewise, the eigenvector for PC3 contained negative loadings for Pa and Mn. The eigenvalue for PC4 was 1.56 and accounted for 8% of the variability. PC4 contained positive loadings for MBN, Na, Fe, and Cu. In addition, PC4 contained negative loadings for Bd and K. PC5 had an eigenvalue of 1.39 and explained 6% of the variability. PC5 included positive loadings for YdI, S, Na, Mn, and Zn. Conversely, PC5 contained negative loading for WAS. PC6 had an eigenvalue of 1.13 and explained 5% of the variability. The eigenvector for PC6 showed positive loadings for Pa and Zn. PC6 also contained negative loadings for YdI, CEC, and Ca. The final PC7 had an eigenvalue of 1.12 and explained 5% of the variability ,while its eigenvector showed positive loadings for Bd, WAS, and Na. These seven significant PCs were used as independent variables in our multiple regression analysis.

Table 2. Principal component analysis based on 52 observations modeling GHG emissions (N_2O, CO_2, and CH_4) with 23 variables, with eigenvalues and the cumulative proportion of the dataset variability explained by the seven principal components (PC) extracted with eigenvalues >1. Component correlation scores (eigenvalues) with loadings greater than |0.25| are in bold.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Eigenvalue	6.04	5.01	2.17	1.56	1.39	1.13	1.12
Cum. Proportion	0.26	0.48	0.58	0.64	0.70	0.75	0.80
Soil Variable	**Component Correlation Scores**						
YdI	0.07	−0.05	**0.37**	0.11	**0.44**	**−0.35**	−0.21
BD	−0.09	0.00	−0.03	**−0.45**	0.07	0.24	**0.60**
WAS	−0.04	0.19	0.07	0.14	**−0.52**	−0.06	**0.27**
pH	**0.32**	−0.21	0.00	−0.18	0.00	0.15	0.05
CEC	−0.22	**0.28**	−0.17	0.20	−0.01	**−0.30**	−0.05
SOM	−0.12	**0.39**	0.16	−0.16	0.08	−0.07	−0.01
C	0.03	**0.39**	0.18	−0.22	0.09	−0.01	0.01
N	−0.17	**0.36**	0.05	−0.21	0.07	−0.09	0.06
C/N	**0.32**	0.11	0.20	−0.03	0.00	0.13	−0.08

Table 2. *Cont.*

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
MBC	0.18	0.14	0.20	−0.12	0.00	0.16	−0.14
MBN	0.14	−0.02	**0.44**	**0.32**	−0.04	0.18	0.19
Pa	0.04	0.19	**−0.25**	0.18	0.22	**0.52**	−0.23
K	−0.19	0.14	−0.14	**−0.28**	−0.06	0.04	−0.10
S	**−0.26**	−0.10	0.07	−0.12	**0.37**	−0.11	0.09
Ca	0.19	**0.30**	−0.09	0.08	0.06	**−0.30**	0.09
Mg	**0.33**	0.12	−0.20	0.03	−0.02	−0.24	0.12
Na	−0.15	−0.10	0.12	**0.29**	**0.32**	−0.01	**0.52**
B	**0.34**	−0.01	−0.05	−0.03	0.14	−0.11	0.19
Fe	−0.25	0.22	0.01	**0.34**	−0.03	0.22	0.04
Mn	−0.03	−0.11	**−0.52**	0.04	**0.29**	−0.04	0.03
Cu	0.23	0.23	−0.25	**0.33**	0.04	0.04	0.22
Zn	0.09	**0.28**	0.04	0.01	**0.31**	**0.32**	−0.04
Al	**−0.35**	−0.11	0.12	0.14	−0.03	0.10	−0.06

3.3. Yield Index 34 Variable Dataset

The PCA of the 34 variable dataset for the yield index rendered a set of eight uncorrelated variables or PCs (PC1 to PC8, Table 3) with eigenvalues larger than 1, which, when added together explained about 83% of the total variability contained in the YdI database. These eight PCs incorporated the 34 original variables but contained high loading factors based on their contributions to variability and correlations with the PC. PC1 had the largest eigenvalue (8.75) and explained around 26% of the variability with its eigenvector that included high positive loadings (>0.25) for CEC and S. In addition PC1 included high negative loadings (<−0.25) for pH and B. PC2 had an eigenvalue of 6.58 and explained around 19% of the variability in the 34 variable set for yield index. The eigenvector for PC2 had positive loadings for PWP, C, Ca, and Cu. The eigenvalue for PC3 was 3.54 and explained an additional 11% of the total variability. The eigenvector for PC3 included positive loadings for CH_4, clay, NH_4, NO_3, and TIN. The eigenvalue for PC4 was 2.62 and accounted for 7% of the variability. PC4 contained positive loadings for PAW, Pa, Mn, and Zn. In addition, PC4 contained a negative loading for WAS. PC5 had an eigenvalue of 2.35 and explained 7% of the variability. PC5 included positive loadings for clay, MBN, Na, and Fe. Conversely, PC5 contained negative loadings for silt, Bd, and Mn. PC6 had an eigenvalue of 1.66 and explained 5% of the variability. The eigenvector for PC6 showed positive loadings for CH_4, sand, MBC, and MBN. The eigenvalue for PC7 was 1.38 and explained an additional 4% of the variability. The eigenvector for PC7 contained positive loadings for Bd, MBN, Na, and Zn. PC7 also contained a negative loading for N_2O. The final PC8 had an eigenvalue of 1.20 and explained 4% of the variability, while its eigenvector showed positive loadings for Bd, Na, and B and a negative loading for Pa. These eight significant PCs were used as independent variables in our multiple regression analysis.

Table 3. Principal component analysis based on 32 observations modeling the yield index with 34 variables, with eigenvalues and cumulative proportion of the dataset variability explained by the eight principal components (PC) extracted with eigenvalues >1. Component correlation scores (eigenvalues) with loadings greater than |0.25| are in bold.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	8.75	6.58	3.54	2.62	2.35	1.66	1.38	1.20
Cum. Proportion	0.26	0.45	0.56	0.63	0.70	0.75	0.79	0.83
Soil Variable	**Component Correlation Scores**							
N_2O	0.20	0.08	0.23	0.18	−0.01	0.07	**−0.26**	0.15
CO_2	0.22	−0.07	0.00	0.21	0.15	0.18	−0.20	0.22
CH_4	0.03	0.05	**0.25**	0.16	−0.07	**0.46**	0.13	−0.12

Table 3. *Cont.*

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Sand	0.20	0.01	−0.02	−0.24	0.07	**0.35**	−0.05	0.05
Silt	−0.08	−0.19	−0.24	0.21	**−0.29**	0.03	0.04	0.05
Clay	0.05	0.20	**0.26**	−0.18	**0.29**	−0.10	−0.03	−0.06
Ho	0.02	0.22	−0.22	−0.09	−0.17	−0.04	−0.17	0.04
PWP	−0.11	**0.29**	−0.14	−0.14	−0.05	−0.06	−0.05	−0.02
PAW	0.13	−0.07	0.14	**0.37**	0.08	−0.12	−0.24	0.16
BD	0.05	−0.03	−0.07	−0.07	**−0.26**	0.13	**0.35**	**0.54**
WAS	0.00	0.18	−0.13	**−0.31**	0.00	−0.22	0.10	0.09
pH	**−0.31**	−0.05	0.12	−0.05	−0.08	0.00	0.04	0.10
CEC	**0.28**	0.14	−0.13	0.04	0.03	−0.10	−0.18	−0.15
SOM	0.21	0.21	−0.25	0.06	0.04	0.10	−0.02	0.12
C	0.11	**0.28**	−0.22	0.10	0.02	0.10	−0.08	0.19
N	0.23	0.20	−0.19	0.00	−0.08	0.04	0.03	0.11
C/N	−0.25	0.15	−0.04	0.12	0.18	0.12	−0.19	0.07
MBC	−0.13	0.11	−0.10	0.13	−0.15	**0.50**	−0.05	−0.15
MBN	−0.16	0.03	0.05	−0.02	**0.38**	**0.31**	**0.31**	−0.06
NH_4	0.16	0.16	**0.28**	−0.13	−0.19	0.06	0.14	−0.06
NO_3	0.18	0.13	**0.35**	−0.04	−0.07	0.01	0.00	0.03
TIN	0.19	0.15	**0.34**	−0.08	−0.12	0.03	0.06	−0.01
Pa	−0.01	0.19	−0.05	**0.35**	−0.03	−0.14	0.22	**−0.38**
K	0.21	0.07	0.10	−0.11	−0.21	−0.10	0.24	−0.02
S	**0.26**	−0.20	0.00	0.08	0.06	−0.02	0.03	0.08
Ca	−0.01	**0.33**	0.02	0.04	0.03	−0.07	0.11	0.16
Mg	−0.22	0.23	0.16	0.02	−0.01	−0.10	−0.10	0.12
Na	0.06	−0.14	0.01	0.14	**0.36**	−0.16	**0.32**	**0.34**
B	**−0.25**	0.08	0.16	0.11	0.09	−0.04	0.03	**0.28**
Fe	0.24	0.11	−0.09	0.14	**0.25**	−0.05	0.13	−0.16
Mn	0.01	−0.09	0.17	**0.30**	**−0.37**	−0.20	0.01	0.00
Cu	−0.12	**0.29**	0.07	0.21	0.10	−0.14	−0.02	0.01
Zn	−0.01	0.20	−0.11	**0.31**	−0.06	−0.01	**0.42**	−0.06
Al	0.23	−0.21	−0.10	−0.05	0.13	−0.06	0.14	−0.18

3.4. Yield Index 25 Variable Dataset

The PCA of the 25 variable dataset for the yield index rendered a set of eight uncorrelated variables or PCs (PC1 to PC8, Table 4) with eigenvalues larger than 1, which, when added together explained about 82% of the total variability contained in the YdI database. These eight PCs incorporated the 25 original variables but contained high loading factors based on their contributions to variability and correlations with the PC. PC1 had the largest eigenvalue (6.73) and explained around 27% of the variability with its eigenvector that included high positive loadings (>0.25) for S and Al. In addition PC1 included high negative loadings (<−0.25) for pH, C/N, Mg, and B. PC2 had an eigenvalue of 5.23 and explained around 21% of the variability in the 25 variable set for yield index. The eigenvector for PC2 had positive loadings for CEC, SOM, C, N, Ca, and Zn. The eigenvalue for PC3 was 2.16 and explained an additional 8% of the total variability. The eigenvector for PC3 included positive loadings for N_2O, CO_2, and Mn. PC3 also contained negative loadings for WAS and MBN. The eigenvalue for PC4 was 1.58 and accounted for 7% of the variability. PC4 contained positive loadings for CH4, MBN, Na, and Fe. In addition, PC4 contained a negative loading for Bd. PC5 had an eigenvalue of 1.48 and explained 6% of the variability. PC5 included positive loadings for N_2O, CH_4, Bd, MBC, and K. Conversely, PC5 contained negative loadings for WAS, CEC, and Cu. PC6 had an eigenvalue of 1.25 and explained 5% of the variability. The eigenvector for PC6 showed positive loadings for N_2O, CO_2, Na, and B. PC6 also contained a negative loading for Pa. The eigenvalue for PC7 was 1.13 and explained an additional 4% of the variability. The eigenvector for PC7 contained positive loadings for Bd, Na, and Zn. PC7 also contained a negative loading for N_2O. The final PC8 had an eigenvalue of 1.01 and explained 4% of the variability, while its eigenvector showed positive loadings for N_2O,

CH_4, WAS, and K. PC8 also had a negative loading for MBC. These eight significant PCs were used as independent variables in our multiple regression analysis.

Table 4. Principal component analysis based on 52 observations modeling the yield index with 25 variables, with eigenvalues and the cumulative proportion of the dataset variability explained by the eight principal components (PC) extracted with eigenvalues >1. Component correlation scores (eigenvalues) with loadings greater than |0.25| are in bold.

	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue	6.73	5.23	2.16	1.58	1.48	1.25	1.13	1.01
Cum. Proportion	0.27	0.48	0.56	0.63	0.69	0.74	0.78	0.82
Soil Variable	**Component Correlation Scores**							
N_2O	0.13	0.15	**0.30**	0.24	**0.26**	**0.29**	**−0.25**	**0.26**
CO_2	0.21	0.10	**0.26**	0.17	0.01	**0.37**	−0.15	−0.06
CH_4	0.00	−0.04	0.09	**0.41**	**0.48**	−0.19	−0.08	**0.33**
BD	0.08	0.01	−0.04	**−0.26**	**0.31**	0.16	0.58	0.11
WAS	0.01	0.15	**−0.27**	−0.11	**−0.28**	−0.19	0.01	**0.59**
pH	**−0.32**	−0.20	0.04	−0.07	0.14	0.01	0.12	0.02
CEC	0.23	**0.28**	0.08	−0.04	**−0.26**	0.01	−0.18	−0.08
SOM	0.12	**0.37**	−0.16	−0.08	0.13	0.12	0.04	−0.09
C	−0.03	**0.38**	−0.18	−0.08	0.17	0.16	0.04	−0.15
N	0.16	**0.35**	−0.11	−0.19	0.10	0.05	0.08	−0.03
C/N	**−0.30**	0.10	−0.12	0.13	0.09	0.12	−0.06	−0.19
MBC	−0.17	0.14	−0.19	0.09	**0.26**	0.04	−0.10	**−0.28**
MBN	−0.13	−0.04	**−0.35**	**0.48**	−0.06	0.09	0.10	0.10
Pa	−0.04	0.19	0.24	0.19	0.04	**−0.51**	0.20	−0.17
K	0.19	0.12	0.11	−0.20	**0.28**	−0.16	0.04	**0.36**
S	**0.32**	−0.11	0.06	0.10	0.04	0.19	0.11	−0.05
Ca	−0.16	**0.32**	0.08	−0.04	−0.17	0.09	0.00	0.13
Mg	**−0.31**	0.15	0.19	−0.08	−0.13	0.13	−0.03	0.18
Na	0.15	−0.10	−0.01	**0.27**	−0.24	**0.32**	**0.52**	0.08
B	**−0.31**	0.01	0.13	0.01	−0.03	**0.26**	0.14	0.09
Fe	0.24	0.20	−0.05	**0.29**	−0.16	−0.16	0.05	−0.08
Mn	0.05	−0.07	**0.54**	−0.13	−0.07	−0.09	0.16	−0.18
Cu	−0.20	0.24	0.23	0.19	**−0.27**	−0.01	0.10	0.09
Zn	−0.10	**0.27**	0.07	0.19	0.10	−0.23	**0.33**	−0.10
Al	**0.33**	−0.13	−0.15	0.11	−0.07	−0.11	0.04	−0.10

3.5. Multiple Regression Analysis

Following extraction of the uncorrelated PCs from each of the datasets, multiple regression analyses were conducted to model each GHG emission type (N_2O, CO_2, and CH_4), and also to model the yield index. Multiple regression analyses were conducted to determine which variables impact GHG emissions and YdI. Modeling of N_2O emissions using the larger (32) variable dataset resulted in three PCs being retained (Table 5). These three PCs explained around 39% of the N_2O variability in the dataset. The PCs retained were PC1, PC3, and PC4. The variables included within each PC are listed in full in Section 3.1 above. Modeling of CO_2 emissions using the 32 variable dataset resulted in five PCs being retained (Table 5). These five PCs explained around 49% of the CO_2 variability in the dataset. The PCs retained were PC1, PC2, PC4, PC6, and PC8. The variables included within each PC are listed in full in Section 3.1 above. Modeling of CH_4 emissions using the 32 variable dataset resulted in only one PC being retained (Table 5). This single PCs explained only around 11% of the CH_4 variability in the dataset. The PC retained was PC6. The variables included within the PC are listed in full in Section 3.1 above. Modeling of YdI emissions using the 34 variable dataset resulted in only one PC being retained (Table 5). This single PCs explained around 12% of the YdI variability in the dataset. The PC retained was PC2. The variable included within the PC is listed in full in Section 3.3

above. The variables chosen to represent the PC component in the N_2O, CO_2, CH_4, and YdI regression equations (listed below) were based on the largest loading values from the retained PCs:

$$N_2O = 0.16 + 0.23(-\mathrm{pH}) - 0.20(-\mathrm{NO_3}) + 0.22(PAW),$$

$$CO_2 = 0.30 + 0.20(-\mathrm{pH}) - 0.09(\mathrm{Ca}) + 0.17(PAW) + 0.20(MBC) + 0.27(PAW),$$

$$CH_4 = 0.02 + 0.30(MBC),$$

$$YdI = -0.55 - 0.14(\mathrm{Ca}).$$

Likewise, using multiple regression analysis modeling of N_2O emissions using the smaller (23) variable dataset resulted in two PCs being retained (Table 5). These 2 PCs only explained around 10% of the N_2O variability in the dataset, a drop of nearly 30% in explanatory capability. The PCs retained were PC1 and PC2. The variables included within each PC are listed in full in Section 3.2 above. Modeling of CO_2 emissions using the 23 variable dataset resulted in two PCs being retained (Table 5). These two PCs explained around 26% of the CO_2 variability in the dataset, a drop of 23% in explanatory capability. The PCs retained were PC1 and PC5. The variables included within each PC are listed in full in Section 3.2 above. Modeling of CH_4 emissions using the 23 variable dataset resulted in only one PC being retained (Table 5). This single PC explained only around 6% of the CH_4 variability in the dataset. The PC retained was PC6. The variables included within the PC are listed in full in Section 3.2 above. Modeling of YdI emissions using the 25 variable dataset resulted in two PCs being retained (Table 5). These PCs explained around 9% of the YdI variability in the dataset. The PCs retained were PC6 and PC8. The variables included within the PCs are listed in full in Section 3.4 above. The variables chosen to represent the PC component in the N_2O, CO_2, CH_4, and YdI regression equations (listed below) were based on the largest loading values from the retained PCs:

$$N_2O = 0.02 - 0.10(-\mathrm{Al}) + 0.12(C),$$

$$CO_2 = 0.02 - 0.18(-\mathrm{Al}) + 0.25(-WAS),$$

$$CH_4 = -0.00092 + 0.27(Pa),$$

$$YdI = -0.08 + 0.23(-Pa) - 0.22(WAS).$$

Table 5. Dependent variables are based on multiple regression analyses of principal components (PC) extracted with eigenvalues >1 and retained in the model (significance level = 0.1500). Dependent variables (nitrous oxide, N_2O; carbon dioxide, CO_2; methane, CH_4; yield index YdI) were modeled using both datasets (PCs are separated by either the 32 or the 52 observation datasets). Variables contained within each PC have component correlation scores (eigenvalues) with loadings greater than |0.25|. Overall adjusted R^2 values represent the amount of variation explained by the regression analysis.

Principal Components Summary Using 32 (for GHG) and 34 (for YdL) Variables							
Dependent Variable	**Retained**	**Estimate**	***p*-Value**	**Variables Contained [1]**	**Stepwise R^2**	**Stepwise *p*-Value**	**Overall Adjusted R^2**
N_2O	PC1	0.20	0.00	pH, CEC, N, C/N, S, B, Fe	0.26	0.00	0.39
	PC3	0.20	0.03	Silt, Clay, SOM, C, NH_4, NO_3, TIN	0.36	0.04	
	PC4	0.22	0.04	Sand, PAW, WAS, Pa, Mn, Zn	0.45	0.04	
CO_2	PC1	0.20	0.00	pH, CEC, N, CN, S, B, Fe	0.31	0.00	0.49
	PC2	0.20	0.08	PWP, C, Ca, Mg, Cu	0.52	0.09	
	PC4	0.17	0.05	Sand, PAW, WAS, Pa, Mn, Zn	0.46	0.06	
	PC6	0.27	0.04	YdI, Sand, WAS, MBC, Na	0.57	0.08	
	PC8	0.09	0.08	PAW, BD, C, Pa	0.39	0.06	
CH_4	PC6	0.30	0.04	YdI, Sand, WAS, MBC, Na	0.14	0.04	0.11
YdI	PC2	0.14	0.03	PWP, C, Ca, Cu	0.15	0.03	0.12
Principal Components Summary Using 23 (for GHG) and 25 (for YdI) Variables							
Dependent Variable	**Retained**	**Estimate**	***p*-Value**	**Variables Contained [2]**	**Stepwise R^2**	**Stepwise *p*-Value**	**Overall Adjusted R^2**
N_2O	PC1	0.12	0.04	pH, C/N, S, Mg, B, Fe, Al	0.14	0.06	0.10
	PC2	0.10	0.06	CEC, SOM, C, N, Ca, Zn	0.08	0.05	
CO_2	PC1	0.18	0.00	pH, C/N, S, Mg, B, Fe, Al	0.21	0.00	0.26
	PC5	0.25	0.02	YdI, WAS, S, Na, Mn, Zn	0.29	0.02	
CH_4	PC6	0.27	0.04	YdI, CEC, Pa, Ca, Zn	0.08	0.04	0.06
YdI	PC6	0.23	0.05	N_2O, CO_2, Pa, Na, B	0.07	0.06	0.09
	PC8	0.22	0.10	N_2O, CH_4, WAS, MBC, K	0.12	0.10	

[1] Variables are listed in full in Tables 1 and 3; [2] Variables are listed in full in Tables 2 and 4.

4. Discussion

4.1. Nitrous Oxide

The results from the multiple regression analysis on the 32 variable dataset reveal that pH, NO_3, and PAW are the variables with the heaviest loadings in the model (Table 5). This means that low pH, increased levels of NO_3, and greater levels of PAW are needed to explain N_2O emissions. Wang, et al. [64] concluded that pH was the chief factor in global a meta-analysis using 1104 field measurements. Their results used a similar multivariate approach to discover that N_2O emissions increase significantly with a decrease in soil pH. We observed a similar result; the CCC-T cropping system emitted greater N_2O emissions compared to other systems (7.67 kg-N ha^{-1} year^{-1}, Appendix A Table A4). Furthermore, the CCC-T rotation had the lowest mean pH (5.08, Appendix A Table A6). Increased levels of NO_3 (similarly NH_4 and TIN contained important loadings in PC3) in the soil provided the necessary substrate for incomplete denitrification, as seen in other N_2O studies [12,18,65]. Likewise, large loadings in PC1 (Table 1) included N and low C/N, which mirrors our results from NO_3. PAW is defined as the difference between the water retained at field capacity and the permanent wilting point, so a higher level of PAW means that the soil can hold more water due to having larger pore spaces. Weier, et al. [65] concluded that the percentage of additional NO_3 lost via denitrification increased with increasing water-filled pore spaces and amounts of C substrate. Important loadings from the retained PC3 include SOM, which furthers the need for C substrate for N_2O emissions. Our model explained around 40% of the variation using these three variables.

Comparing the results from the 32 variable dataset, we see a large decrease in the total amount of variation explained, down from 40% in the 32 variable dataset, to 10% in the 23 variable dataset (Table 5).

The 23 variable dataset contained only variables with equal comparisons; the loss of sand, silt, clay, Ho, PWP, PAW, NH_4, NO_3, and TIN reduced the ability to explain N_2O emissions by 30%. Exclusion of soil water dynamics and soil nitrogen intensity variables led to this loss in ability. The multiple regression analysis on the 23 variable dataset revealed that Al and C are the variables with the heaviest loadings in the model. The combination of these variables means that low levels of Al and increased levels of C are needed to explain N_2O emissions. In terms of understanding the Al dynamics occurring in this model, the means table reveals that the soybean rotation had lower values of Al compared to corn (586.38 mg kg^{-1} compared to 670.78 mg kg^{-1}, respectively; Appendix A Table A8). This is further verified by the increased pH values (also heavy loading in PC1, Table 2) occurring in the soybean rotations (7.13 compared to 5.34, respectively; Appendix A Table A6). Likewise, the CCC rotations had significantly greater emissions of N_2O compared to SSS (6.18 kg-N ha^{-1} $year^{-1}$ compared to 0.97 kg-N ha^{-1} $year^{-1}$; Appendix A Table A4) [17]. The effects of low pH are conveyed indirectly in this model, and can also be observed in the recent meta-analysis conducted by Wang, et al. [64]. Other studies conducted on similar soils have observed that N_2O emissions occur in greater amounts when given an increased level of C substrate [65]. In addition, SOM is an important loading in PC2, which has a similar effect to adding C substrate.

4.2. Carbon Dioxide

The results from the multiple regression analysis on the 32 variable dataset reveal that pH, Ca, PAW, and MBC are the variables with the heaviest loadings in the model (Table 5). Thus, low pH, low Ca, increased PAW, and higher levels of MBC are needed to explain CO_2 emissions. Linn and Doran [66] discovered that CO_2 production increases as water-filled pore spaces are filled, regardless of the application of N fertilizer. As PAW increases, water is more prevalent in the soil, which can lead to CO_2 evolution through increased microbial activity. During wheat production, Lupwayi, et al. [67] observed that microbial biomass is more dynamic compared to SOM, and changes in management may be reflected more clearly in MBC compared to SOM. The authors also observed that the amount of MBC is directly related to CO_2 evolution; a similar observation was seen by Linn and Doran [66], albeit with microbial activity and not MBC specifically. Low pH and low Ca levels in the soil negatively affect the levels of MBC, which limits the production of CO_2. Likewise, in environments with low pH levels, Ca is able to leach through the soil [68]. Our model explained around 50% of the variation using these five variables.

Compared with results from the 32 variable dataset, there was a large decrease in the total amount of variation explained, down from 50% in the 32 variable dataset, to 26% in the 23 variable dataset. The 23 variable dataset was reduced by nine variables and decreased the ability to explain CO_2 emissions by 24%. The multiple regression analysis on the 23 variable dataset revealed that Al and WAS are the variables with the heaviest loadings in the model (Table 5). The combination of these variables means that high levels of aluminum and lower WAS are needed to explain CO_2 emissions. Al is more available at a lower pH. Similar to the N_2O model, when observing the means table, the soybean rotation had lower values of Al compared to corn (586.38 mg kg^{-1} compared to 670.78 mg kg^{-1}, respectively; Appendix A Table A8). This was further verified by the increased pH values (also heavy loading in PC1, Table 2) occurring in the soybean rotations (7.13 compared to 5.34, respectively; Appendix A Table A6). Likewise, the CCC rotations had significantly greater emissions of CO_2 compared to SSS (4.43 Mg-N ha^{-1} $year^{-1}$ compared to 2.63 kg-N ha^{-1} $year^{-1}$; Appendix A Table A4) [17]. Increases in WAS are related to the protection of SOM. The destruction of stable aggregates (WAS) causes decomposition of SOM and greater CO_2 emissions [69]. Our model explained around 26% of the variation using only these two variables.

4.3. Methane

The results from the multiple regression analysis on the 32 variable dataset reveal that MBC is the variable with the heaviest loading in the model (Table 5). This means that a larger MBC concentration leads to increased CH_4 production. Methane produced from agricultural practices has been found to be emitted biologically via methanogenic bacteria under anaerobic soil conditions [70,71]. Methane has also been found to be consumed in agricultural soils by soil methanotropic bacteria [72]. This phenomenon causes agricultural soils (excluding rice paddies) to be consumers, producers or neutral, depending on the time of season [71]. It is not surprising that the biological nature of CH_4 production is explained best by MBC. The means for CH_4 show the largest emissions from the CCC rotation compared to the other rotations (0.43 kg-C ha^{-1} year^{-1}, CCC; 0.25 kg-C ha^{-1} year^{-1}, CS; 0.22 kg-C ha^{-1} year^{-1}, CSW; and 0.24 kg-C ha^{-1} year^{-1}, SSS) (Appendix A Table A4); however, MBC is the lowest in CCC compared to the other rotations (54.69 µg g^{-1}, CCC; 67.27 µg g^{-1}, CS; 70.72 µg g^{-1}, CSW; and 77.38 µg g^{-1}, SSS) (Appendix A Table A6). On similar Mollisols in Ohio, Jacinthe and Lal [73] observed that increased CH_4 uptake in soils occurs with greater MBC concentrations. Our model explained around 11% of the variation using this one variable.

Compared with the results from the 32 variable dataset, there was a decrease in the total amount of variation explained, down from 11% in the 32 variable dataset, to 6% in the 23 variable dataset. The multiple regression analysis on the 23 variable dataset revealed that Pa was the variable with the heaviest loading in the model (Table 5). This means that higher values of Pa are needed to explain CH_4 emissions. Our model explained around 6% of the variation using this one variable.

4.4. Yield Index

The results from the multiple regression analysis on the 34 variable dataset reveal that Ca is the variable with the heaviest loading in the model (Table 5). This single variable means that lower Ca concentrations lead to an increased YdI. Since the YdI variable is standardized by cash crop to a mean of 0 and a standard deviation of 1, direct comparisons are difficult to interpret. However, looking at the YdI means (Appendix A Table A4) reveals that larger YdI values occur in the crop rotations (0.27, CS and 0.19, CSW) relative to the monocultures (−0.74, CCC and −0.26, SSS). Using the same yield data, Behnke, et al. [17] found that crop rotation increased the yields of corn and soybean in the CS rotation compared to either the CCC and SSS monocultures. Since wheat was not grown continuously, a wheat comparison was not possible. As yield levels increase, Ca concentration in the removed grain increases [74]. However, Ca levels seem to be weakly correlated with crop rotation, though the crop rotations do have smaller standard errors compared to the CCC and SSS monocultures. However, the CSW rotation did have the largest values (Appendix A Table A7). Since these soils are naturally high in Ca and were limed every two years, following the guidelines in the Illinois Agronomy Handbook [48], levels of Ca are likely not limiting. Our model explained around 12% of the variation using this one variable.

When looking at the results from the 34 variable dataset, we can see a small decrease in the total amount of variation explained—9% in the 25 variable dataset. The multiple regression analysis on the 23 variable dataset reveals that Pa and WAS are the variables with the heaviest loadings in the model (Table 5). Thus, low levels of Pa and lower WAS are needed to explain YdI. Similar to Ca in the 34 variable dataset, as yield levels increase, greater amounts of Pa are removed by the grain [74]. Therefore, as YdI levels increase less Pa will remain in the soil. The YdIs of the crop rotations (CS and CSW; Appendix A Table A4) are greater compared to the monocultures (CCC and SSS; Appendix A Table A4). This can be as attributed to the levels of Pa in the crop rotations (8.59 mg ka^{-1}, CS and 9.87 mg kg^{-1}, CSW; Appendix A Table A7) being lower compared to those in the monocultures (13.56 mg kg^{-1}, CCC and 17.50 mg kg^{-1}, SSS; Appendix A Table A7). Trends in WAS are less evident as the crop rotations had similar WAS means (Appendix A Table A5). The trends in WAS may be more related to the tillage implementation as WAS levels from tilled treatments were lower than their NT counterparts (0.82 g g^{-1}, T and 0.85 g g^{-1}, NT; Appendix A Table A5). Comparing this to the T and NT YdI levels, an inverse relationship exists (0.22, T and −0.18 NT; Appendix A Table A4). Behnke, et al. [17] observed a significant yield increase due to tillage used as a means of managing the high amount of corn residue produced in high organic matter soils. Other studies in the Midwest confirm an increase in yield due to tillage as well [24,25]. Long-term (5+ years) NT corn systems are routinely subject to reductions in yields [27] due to waterlogging and poor establishment, compaction, and nutrient deficiencies [24,28,29]. Villamil, et al. [75] concluded that in highly productive and highly resilient Illinois systems, tillage does not pose a threat to soil quality.

This multivariate analysis was conducted using data from Illinois on highly productive soils from different cropping systems with the objective of investigating the relationships among GHG emissions, yields, and soil properties. The two datasets including differing numbers of variables highlight the importance of utilizing data with and without missing data points. The dataset with more variables contained missing data, while the dataset containing fewer variables contained paired data with no missing data. Both datasets are important in discovering which variables are important predictors for GHG emissions and the yield index.

5. Conclusions

Overall, our analysis showed the complex relationships among GHG emissions, yield and soil properties. Increased N_2O emissions were correlated to low pH conditions (and an increased Al concentration), the presence of soil NO_3 throughout the growing season, an increase in plant available water and an increased C concentration. Lower soil pH was evident in the CCC rotation compared to the other rotations; CCC also had greater N_2O emissions. Greater CO_2 emissions were related to low pH (or high Al concentrations), low levels of Ca, increased PAW, higher levels of MBC, and lower WAS. Methane emissions reveal that higher levels of MBC lead to lower CH_4 emissions due to methane uptake from soil microbes. Lastly, increased levels of YdI were correlated with lower levels of soil Ca and Pa and lower values of WAS. It is important to note that lower levels of WAS were seen in the T treatments compared to the NT treatments. Likewise, the NT YdI was lower than the T YdI. Therefore increases in YdI can be attributed to tillage more than to lower levels of WAS, as is typical in highly productive Midwest cropping systems. The results from this study describe the influences that crop rotation and tillage have on the modeling of GHG emissions and yields. Our results indicate the benefits of utilizing a crop rotation compared to a monoculture. The results include a decrease in N_2O emissions and an increase in yield. This study will add valuable information to the understanding of how interconnected numerous soil properties are to GHG emissions and yield.

Author Contributions: M.B.V. and E.D.N. conceived and designed the experiments and contributed reagents/materials/analysis tools; G.D.B performed the experiments; M.B.V. and G.D.B. analyzed the data; and G.D.B. and M.B.V. wrote the paper while C.M.P. provided additional guidance and critical and constructive feedback.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table A1. Field event dates from Monmouth, IL throughout the duration of the study. Wheat plot operations began in the previous year due to fall planting.

Field Event Type	2012	2013	2014	2015
Tilled wheat plots [1]	3 October 2011	28 September 2012	2 October 2013	7 October 2014
Planting date of all wheat plots	3 October 2011	28 September 2012	3 October 2013	7 October 2014
Fall wheat fertilization	24 October 2011	17 October 2012	21 October 2013	1 November 2014
Fall tillage of corn and soybean plots [1]	8 November 2011	9 November 2012	4 November 2013	14 November 2014
Spring wheat fertilization	20-Mar-2012	5 April 2013	11 April 2014 [3]	1 April 2015
Secondary tillage in corn and soybean plots [2]	4 April 2012	1 May 2013	18 April 2014	24 April 2015
Spring corn fertilization	18 April 2012	17 May 2013	22 April 2014	1 May 2015
Planting date of all corn plots	18 April 2012	16 May 2013	22 April 2014	1 May 2015
Planting date of all soybean plots	10 May 2012	24 May 2013	22 May 2014 [4]	13 May 2015
Harvest of all wheat plots	20 June 2012	10 July 2013	31 July 2014	10 July 2015
Harvest of all corn plots	24 September 2012	2 October 2013	30 September 2014	23 September 2015
Harvest of all soybean plots	27 September 2012	2 October 2013	7 October 2014	24 September 2015

[1] Chisel tillage used a disk-ripper 36-cm deep in plots designated as tilled; no-till received zero tillage. [2] Secondary tillage used a field cultivator in plots designated as tilled; no-till received zero tillage. [3] Winter wheat crop was terminated due to poor stands stemming from harsh winter conditions; spring oats were planted 17 April 2014 and fertilized 11 April 2014. [4] Soybean plots receiving tillage had secondary tillage on 8 May 2014.

Table A2. Number of GHG sampling events from Monmouth, IL by year and season.

Season [1]	Number of Observations			
	2012	2013	2014	2015
Spring	8	2	4	5
Summer	9	9	8	13
Fall	1	3	2	3

[1] Spring, March-May; Summer, June–August; Fall, September–November.

Table A3. Number of observations, season of sampling, and year of sampling originally included for each variable throughout the study (2012–2015) from Monmouth, IL.

Variable	No. of Obs.	Season of Sampling [1]	Year(s) of Sampling
YdI	192	Summer & Fall	2012–2015
N_2O	2531	Spring, Summer, Fall & Winter	2012–2015
CO_2	2531	Spring, Summer, Fall & Winter	2012–2015
CH_4	2531	Spring, Summer, Fall & Winter	2012–2015
Sand	176	Spring	2012
Silt	176	Spring	2012
Clay	176	Spring	2012
Ho	1970	Spring, Summer, Fall & Winter	2013–2015
PWP	192	Spring	2012
PAW	192	Spring	2012
BD	336	Spring	2014
WAS	336	Spring	2014

Table A3. *Cont.*

Variable	No. of Obs.	Season of Sampling [1]	Year(s) of Sampling
pH	112	Spring	2014
CEC	112	Spring	2014
SOM	112	Spring	2014
C	112	Spring	2014
N	112	Spring	2014
C/N	112	Spring	2014
MBC	224	Spring	2014
MBN	224	Spring	2014
NH_4	1970	Spring, Summer, Fall & Winter	2013–2015
NO_3	1970	Spring, Summer, Fall & Winter	2013–2015
TIN	1970	Spring, Summer, Fall & Winter	2013–2015
Pa	112	Spring	2014
K	112	Spring	2014
S	112	Spring	2014
Ca	112	Spring	2014
Mg	112	Spring	2014
Na	112	Spring	2014
B	112	Spring	2014
Fe	112	Spring	2014
Mn	112	Spring	2014
Cu	112	Spring	2014
Zn	112	Spring	2014
Al	112	Spring	2014

[1] Spring, March–May; Summer, June–August; Fall, September–November; Winter, December–February.

Table A4. Mean values of yield index (YdI), nitrous oxide (N_2O, kg-N ha^{-1} year^{-1}), carbon dioxide (CO_2, Mg-C ha^{-1} year^{-1}), and methane (CH_4, kg-C ha^{-1} year^{-1}), determined by crop rotation (R) and tillage (T) and for each R and T combination.

Crop Rotation (R)	Tillage (T)	YdI		N_2O		CO_2		CH_4	
		Mean	SEM [1]	Mean	SEM	Mean	SEM	Mean	SEM
CCC		−0.74	0.11	6.18	0.73	4.43	0.42	0.43	0.07
CS		0.27	0.09	2.42	0.15	3.57	0.22	0.25	0.07
CSW		0.19	0.07	2.17	0.35	2.98	0.28	0.22	0.09
SSS		−0.26	0.12	0.97	0.14	2.63	0.15	0.24	0.12
	T [2]	0.22	0.08	3.26	0.41	3.63	0.24	0.31	0.05
	NT	−0.18	0.10	2.00	0.33	2.97	0.20	0.21	0.09
Rotation × Tillage									
CCC [3]	T	−0.46	0.04	7.67	0.83	5.11	0.68	0.52	0.07
CCC	NT	−1.02	0.07	4.69	0.59	3.75	0.18	0.34	0.11
CS	T	0.64	0.12	2.06	0.12	3.47	0.47	0.13	0.09
CS	NT	0.23	0.02	2.06	0.33	3.35	0.24	0.08	0.19
CSW	T	0.09	0.05	3.17	0.53	4.85	0.25	0.07	0.06
CSW	NT	−0.35	0.02	0.97	0.06	2.96	0.29	−0.03	0.30
SC	T	0.28	0.20	2.43	0.13	3.89	0.52	0.34	0.08
SC	NT	−0.06	0.16	3.12	0.21	3.57	0.63	0.45	0.12
SWC	T	0.43	0.09	2.33	0.36	2.30	0.22	0.43	0.17
SWC	NT	−0.09	0.07	0.34	0.09	1.46	0.16	0.29	0.32
SSS	T	0.01	0.11	1.10	0.24	2.49	0.19	0.34	0.17
SSS	NT	−0.53	0.10	0.85	0.17	2.76	0.24	0.14	0.17
WCS	T	0.52	0.03	4.07	0.64	3.32	0.24	0.34	0.08
WCS	NT	0.53	0.10	_ [4]	_	_	_	_	_

[1] SEM, standard error of the mean values; [2] T, chisel till; NT, no-till; [3] CCC, continuous corn; CS, corn-soybean; CSW, corn-soybean-wheat; SC, soybean-corn; SWC, soybean-wheat-corn; SSS continuous soybean; WCS, wheat-corn-soybean; [4] _, no samples taken.

Table A5. Mean values of sand (%), silt (%), clay (%), average soil moisture (Ho, %), permanent wilting point (PWP, $cm^3\ cm^{-3}$), plant available water (PAW, $cm^3\ cm^{-3}$), bulk density (Bd, $Mg\ m^{-3}$), water aggregate stability (WAS, $g\ g^{-1}$), determined by crop rotation (R) and tillage (T) and for each R and T combination.

Crop Rotation (R)	Tillage (T)	Sand		Silt		Clay		Ho		PWP		PAW		Bd		WAS	
		Mean	SEM [1]	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM
CCC		2.50	0.16	70.44	0.39	27.06	0.37	18.51	0.23	0.11	0.00	0.35	0.01	1.37	0.03	0.84	0.02
CS		2.47	0.12	71.22	0.66	26.31	0.69	17.45	0.21	0.10	0.00	0.34	0.01	1.34	0.02	0.83	0.01
CSW		2.50	0.12	72.19	0.50	25.31	0.52	18.83	0.81	0.11	0.00	0.31	0.01	1.35	0.02	0.84	0.01
SSS		2.00	0.00	72.31	0.69	25.69	0.69	17.34	0.42	0.11	0.00	0.31	0.01	1.33	0.02	0.82	0.02
	T [2]	2.44	0.10	71.48	0.44	26.08	0.47	17.75	0.41	0.10	0.00	0.34	0.01	1.32	0.01	0.82	0.01
	NT	2.38	0.09	71.71	0.45	25.92	0.45	18.51	0.43	0.11	0.00	0.32	0.01	1.37	0.02	0.85	0.01
Rotation × Tillage																	
CCC [3]	T	2.50	0.29	70.50	0.54	27.00	0.46	18.47	0.34	0.11	0.00	0.37	0.01	1.32	0.01	0.81	0.02
CCC	NT	2.50	0.20	70.38	0.66	27.13	0.66	18.55	0.35	0.11	0.00	0.33	0.02	1.42	0.03	0.87	0.01
CS	T	2.63	0.38	71.00	1.49	26.38	1.70	17.23	0.21	_	_	_	_	1.34	0.03	0.83	0.03
CS	NT	2.75	0.14	71.00	1.54	26.25	1.65	18.09	0.29	_	_	_	_	1.34	0.03	0.86	0.03
CSW	T	2.38	0.13	72.25	1.05	25.38	1.11	17.46	0.41	0.11	0.00	0.33	0.00	1.34	0.04	0.83	0.02
CSW	NT	2.50	0.29	72.13	0.94	25.38	0.72	21.13	1.27	0.12	0.01	0.30	0.02	1.40	0.04	0.89	0.02
SC	T	2.25	0.14	71.00	1.47	26.75	1.45	17.24	0.39	0.10	0.00	0.36	0.02	1.29	0.02	0.85	0.01
SC	NT	2.25	0.14	71.88	1.34	25.88	1.33	17.23	0.64	0.11	0.01	0.32	0.02	1.41	0.06	0.80	0.02
SWC	T	_ [4]	_	_	_	_	_	14.81	0.27	_	_	_	_	1.28	0.02	0.81	0.03
SWC	NT	_	_	_	_	_	_	_	_	_	_	_	_	1.36	0.07	0.83	0.02
SSS	T	2.00	0.00	72.25	1.09	25.75	1.09	17.10	0.68	0.11	0.00	0.32	0.02	1.30	0.01	0.79	0.02
SSS	NT	2.00	0.00	72.38	1.03	25.63	1.03	17.57	0.57	0.11	0.00	0.31	0.02	1.36	0.03	0.86	0.02
WCS	T	2.88	0.24	71.88	1.11	25.25	1.23	21.93	0.51	_	_	_	_	1.38	0.03	0.81	0.03
WCS	NT	2.25	0.25	72.50	1.32	25.25	1.44	_	_	_	_	_	_	1.35	0.03	0.85	0.02

[1] SEM, standard error of the mean values; [2] T, chisel till; NT, no-till; [3] CCC, continuous corn; CS, corn-soybean; CSW, corn-soybean-wheat; SC, soybean-corn; SWC, soybean-wheat-corn; SSS continuous soybean; WCS, wheat-corn-soybean; [4] _, no samples taken.

Table A6. Mean values of pH, cation exchange capacity (CEC, $cmol\ kg^{-1}$), soil organic matter (SOM, %), carbon (C, %), nitrogen (N, %), carbon to nitrogen ratio (C/N), microbial biomass carbon (MBC, $\mu g\ g^{-1}$), and microbial biomass nitrogen (MBN, $\mu g\ g^{-1}$), determined by crop rotation (R) and tillage (T) and for each R and T combination.

Crop Rotation (R)	Tillage (T)	pH		CEC		SOM		C		N		C/N		MBC		MBN	
		Mean	SEM [1]	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM
CCC		5.34	0.19	39.36	2.13	4.06	0.07	2.62	0.07	0.21	0.00	12.82	0.21	54.69	5.60	4.06	0.69
CS		6.19	0.18	29.58	2.00	3.77	0.08	2.45	0.06	0.19	0.01	13.47	0.24	67.27	8.00	7.55	1.37
CSW		6.23	0.14	28.80	1.38	4.08	0.09	2.72	0.06	0.20	0.00	13.90	0.20	70.72	6.88	7.09	0.69
SSS		7.13	0.16	22.77	1.04	3.39	0.16	2.32	0.14	0.17	0.01	14.13	0.44	77.38	18.42	7.73	0.88
	T [2]	6.29	0.17	29.62	1.60	3.79	0.09	2.52	0.06	0.19	0.00	13.69	0.23	68.45	7.69	6.96	0.84
	NT	6.16	0.13	29.72	1.43	3.98	0.08	2.63	0.06	0.20	0.00	13.62	0.16	68.34	5.12	6.81	0.65
Rotation × Tillage																	
CCC [3]	T	5.08	0.21	41.51	2.62	3.96	0.08	2.51	0.06	0.20	0.00	12.60	0.30	48.91	6.10	3.92	1.14
CCC	NT	5.60	0.29	37.22	3.34	4.17	0.09	2.74	0.11	0.22	0.00	13.05	0.28	60.46	9.32	4.19	0.94
CS	T	5.78	0.32	37.40	3.63	3.83	0.09	2.48	0.09	0.20	0.01	12.87	0.37	62.33	14.72	7.53	4.40
CS	NT	5.76	0.24	33.97	2.78	4.09	0.11	2.63	0.04	0.20	0.01	13.52	0.46	72.08	10.06	3.37	1.08
CSW	T	5.87	0.36	32.72	3.69	4.26	0.27	2.81	0.14	0.21	0.01	13.70	0.37	65.96	6.77	2.90	0.81
CSW	NT	5.75	0.49	36.23	5.14	4.24	0.21	2.76	0.10	0.22	0.01	13.06	0.35	62.87	8.65	4.57	1.03
SC	T	6.75	0.33	23.22	1.54	3.45	0.18	2.27	0.15	0.17	0.01	13.83	0.62	44.85	8.30	8.34	1.78
SC	NT	6.47	0.32	23.72	2.26	3.70	0.12	2.44	0.15	0.18	0.01	13.67	0.51	89.84	23.21	10.98	1.94
SWC	T	6.80	0.21	23.63	1.73	3.76	0.27	2.48	0.26	0.18	0.01	13.76	0.63	94.17	39.34	9.33	0.95
SWC	NT	6.37	0.21	25.57	1.42	3.77	0.23	2.55	0.19	0.19	0.01	13.88	0.48	63.02	14.78	7.90	1.11
SSS	T	7.33	0.20	22.28	1.72	3.21	0.18	2.23	0.16	0.16	0.01	14.34	0.74	88.83	32.97	7.36	1.70
SSS	NT	6.94	0.25	23.26	1.39	3.56	0.27	2.41	0.24	0.17	0.01	13.92	0.58	65.94	20.22	8.11	0.78
WCS	T	6.40	0.34	26.59	1.56	4.08	0.06	2.84	0.08	0.20	0.00	14.74	0.67	74.14	4.98	9.34	1.81
WCS	NT	6.21	0.30	28.08	1.69	4.37	0.15	2.87	0.06	0.21	0.01	14.27	0.21	64.18	3.76	8.53	1.50

[1] SEM, standard error of the mean values; [2] T, chisel till; NT, no-till; [3] CCC, continuous corn; CS, corn-soybean; CSW, corn-soybean-wheat; SC, soybean-corn; SWC, soybean-wheat-corn; SSS continuous soybean; WCS, wheat-corn-soybean.

Table A7. Mean values of soil ammonia intensity (NH_4, mg-N $kg^{-1}day^{-1}$ during the growing season), soil nitrate intensity (NO_3, mg-N $kg^{-1}day^{-1}$ during the growing season), total soil nitrogen intensity(TIN, mg-N $kg^{-1}day^{-1}$ during the growing season), available phosphorus (Pa, mg kg^{-1}), potassium (K, mg kg^{-1}), sulfur (S, mg kg^{-1}), calcium (Ca, mg kg^{-1}), magnesium (Mg, mg kg^{-1}), and sodium (Na, mg kg^{-1}), determined by crop rotation (R) and tillage (T) and for each R and T combination.

Crop	**Tillage**	**NH_4**		**NO_3**		**TIN**		**Pa**		**K**		**S**		**Ca**		**Mg**		**Na**	
Rotation (R)	**(T)**	**Mean**	**SEM [1]**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**
CCC		3.00	0.76	6.00	1.01	9.00	1.72	13.56	1.27	196.94	19.92	8.09	0.33	3515.06	156.59	436.47	24.29	16.97	1.26
CS		1.10	0.17	2.57	0.24	3.67	0.35	8.59	1.13	146.52	7.76	7.47	0.27	3503.31	115.83	459.48	15.40	18.98	0.62
CSW		1.55	0.40	3.46	0.68	5.03	0.87	9.87	0.90	164.48	8.55	7.56	0.31	3560.91	86.90	440.49	14.20	17.06	0.59
SSS		0.53	0.04	1.44	0.13	1.98	0.16	17.50	4.00	134.31	12.97	6.56	0.22	3352.00	149.92	488.31	18.77	17.13	0.85
	T [2]	1.37	0.21	3.37	0.43	4.75	0.57	11.12	1.14	150.71	7.27	7.52	0.18	3490.98	81.57	461.17	11.77	17.76	0.48
	NT	1.61	0.43	3.09	0.59	4.70	0.97	11.12	1.30	168.63	9.03	7.42	0.29	3525.13	83.23	443.18	13.02	17.46	0.61
Rotation × Tillage																			
CCC [3]	T	2.45	0.56	5.03	0.50	7.48	0.74	13.50	1.65	195.25	11.74	8.44	0.56	3348.63	203.94	419.06	35.47	16.31	1.96
CCC	NT	3.56	1.48	6.97	1.97	10.53	3.43	13.63	2.18	198.63	41.38	7.75	0.32	3681.50	233.17	453.88	35.96	17.63	1.82
CS	T	1.04	0.33	1.72	0.06	2.77	0.36	12.13	3.13	145.31	21.48	8.00	0.31	3873.25	189.36	502.13	32.55	19.94	0.50
CS	NT	0.98	0.39	2.66	0.47	3.64	0.83	9.50	1.58	161.00	11.33	7.00	0.54	3697.63	137.35	459.00	20.55	18.50	1.72
CSW	T	0.81	0.17	1.96	0.31	2.85	0.46	9.69	0.84	168.63	24.50	7.63	0.38	3625.88	195.37	445.19	34.74	17.19	0.90
CSW	NT	1.88	1.22	1.53	0.44	3.41	1.51	12.06	3.82	195.19	27.81	7.06	0.66	3614.94	141.44	429.88	33.57	15.81	1.82
SC	T	1.28	0.41	3.33	0.50	4.60	0.78	5.75	1.45	125.38	16.29	7.19	0.47	3270.19	205.04	459.50	32.93	18.25	0.63
SC	NT	1.09	0.35	2.58	0.46	3.67	0.68	7.00	1.75	154.38	10.47	7.69	0.79	3172.19	242.28	417.31	31.24	19.25	1.90
SWC	T	1.47	1.01	4.14	0.39	5.61	0.87	6.87	1.15	128.75	5.88	7.31	0.37	3469.81	264.08	451.63	33.86	17.75	1.31
SWC	NT	_ [4]	_	_	_	_	_	9.56	2.81	139.00	6.67	7.31	0.73	3491.44	345.90	426.56	53.94	16.13	1.68
SSS	T	0.51	0.04	1.19	0.08	1.70	0.07	18.38	5.13	125.38	9.36	6.50	0.35	3320.88	277.88	499.50	16.49	16.13	1.16
SSS	NT	0.55	0.08	1.69	0.18	2.25	0.26	16.62	6.93	143.25	25.38	6.63	0.31	3383.13	164.38	477.13	35.91	18.13	1.16
WCS	T	2.06	0.58	6.20	2.02	8.26	2.38	11.56	1.60	166.31	17.11	7.56	0.39	3528.25	162.95	451.19	30.26	18.75	1.61
WCS	NT	_	_	_	_	_	_	9.50	2.19	189.00	21.30	8.50	1.59	3635.13	253.66	438.50	42.11	16.75	1.60

[1] SEM, standard error of the mean values; [2] T, chisel till; NT, no-till; [3] CCC, continuous corn; CS, corn-soybean; CSW, corn-soybean-wheat; SC, soybean-corn; SWC, soybean-wheat-corn; SSS continuous soybean; WCS, wheat-corn-soybean; [4] _, no samples taken.

Table A8. Mean values of boron (B, mg kg^{-1}), iron (Fe, mg kg^{-1}), manganese (Mn, mg kg^{-1}), copper (Cu, mg kg^{-1}), zinc (Zn, mg kg^{-1}), and aluminum (Al, mg kg^{-1}), determined by crop rotation (R) and tillage (T) and for each R and T combination.

Crop Rotation (R)	Tillage (T)	B		Fe		Mn		Cu		Zn		Al	
		Mean	**SEM** [1]	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**	**Mean**	**SEM**
CCC		0.60	0.04	158.41	10.26	82.28	5.14	3.02	0.23	2.54	0.16	670.78	47.55
CS		0.68	0.02	125.84	6.24	75.06	4.00	2.89	0.14	2.52	0.08	627.88	24.08
CSW		0.66	0.02	125.95	5.54	66.34	2.07	2.73	0.06	2.76	0.09	638.67	20.51
SSS		0.70	0.02	113.81	8.52	80.75	4.33	3.16	0.20	2.66	0.23	586.38	36.09
	T [2]	0.67	0.02	120.71	4.95	76.04	2.97	2.85	0.09	2.56	0.09	624.25	18.52
	NT	0.65	0.02	136.94	5.54	70.29	2.27	2.90	0.10	2.72	0.08	641.15	21.13
Rotation × Tillage													
CCC [3]	T	0.59	0.07	156.44	15.79	88.81	1.57	2.93	0.36	2.40	0.24	680.19	78.85
CCC	NT	0.61	0.03	160.38	15.46	75.75	9.62	3.10	0.34	2.68	0.23	661.38	65.38
CS	T	0.66	0.03	122.50	10.58	83.44	10.13	3.12	0.31	2.53	0.16	606.38	35.16
CS	NT	0.66	0.02	131.63	11.94	73.38	8.12	2.93	0.27	2.61	0.23	603.63	40.22
CSW	T	0.67	0.03	120.81	13.77	66.06	7.19	2.66	0.15	2.64	0.20	628.75	46.33
CSW	NT	0.59	0.05	141.81	20.13	71.81	4.32	2.79	0.23	2.68	0.09	675.81	71.43
SC	T	0.70	0.05	114.31	11.18	72.19	7.77	2.70	0.25	2.43	0.16	639.06	48.08
SC	NT	0.72	0.03	134.94	17.70	71.25	7.68	2.81	0.35	2.51	0.10	662.44	75.13
SWC	T	0.69	0.04	103.00	5.40	73.81	7.08	2.69	0.18	2.39	0.23	624.81	65.73
SWC	NT	0.67	0.07	130.94	11.53	66.13	2.16	2.63	0.23	2.70	0.22	660.69	60.98
SSS	T	0.71	0.02	106.13	9.80	86.50	7.63	3.07	0.29	2.59	0.32	579.88	47.73
SSS	NT	0.69	0.03	121.50	14.25	75.00	2.68	3.24	0.32	2.74	0.38	592.88	61.42
WCS	T	0.68	0.04	121.75	11.23	61.50	3.47	2.80	0.08	2.97	0.27	610.69	33.91
WCS	NT	0.65	0.04	137.38	14.17	58.75	1.98	2.81	0.13	3.17	0.11	631.25	43.75

[1] SEM, standard error of the mean values; [2] T, chisel till; NT, no-till; [3] CCC, continuous corn; CS, corn-soybean; CSW, corn-soybean-wheat; SC, soybean-corn; SWC, soybean-wheat-corn; SSS continuous soybean; WCS, wheat-corn-soybean.

Table A9. Pearson correlation matrix among greenhouse gas emissions, yield index, and soil physical and chemical properties from Monmouth, IL. Variable include yield index (YdI), nitrous oxide (N_2O), carbon dioxide (CO_2), methane (CH_4), yield index (YdI), sand, silt, clay, average soil moisture (Ho), permanent wilting point (PWP), plant available water (PAW), bulk density (Bd), water aggregate stability (WAS), pH, cation exchange capacity (CEC), soil organic matter (SOM), carbon (C), nitrogen (N), carbon to nitrogen ratio (C/N), microbial biomass carbon (MBC), microbial biomass nitrogen (MBN), soil ammonia intensity (NH_4), soil nitrate intensity (NO_3), total soil nitrogen intensity(TIN), available phosphorus (Pa), potassium (K), sulfur (S), calcium (Ca), magnesium (Mg), sodium (Na), boron, (B), iron (Fe), manganese (Mn), copper (Cu), zinc (Zn), and aluminum (Al).

	YdI	N2O	CO2	CH4	Sand	Silt	Clay	Ho	PWP	PAW	BD	WAS	pH	CEC	SOM	C	N	C/N	MBC	MBN	NH4	NO3	TIN	Pa	K	Sul	Ca	Mg	Na	Bor	Fe	Mn	Cu	Zn	Al
YdI	1.00																																		
N2O	−0.19	1.00																																	
CO2	−0.01	0.59	1.00																																
CH4	0.03	0.30	0.03	1.00																															
Sand	0.12	0.15	0.24	0.07	1.00																														
Silt	0.10	−0.26	0.09	−0.09	−0.01	1.00																													
Clay	−0.13	0.23	−0.14	0.07	−0.20	−0.98	1.00																												
Ho	−0.13	0.14	0.03	−0.09	0.22	0.01	−0.05	1.00																											
PWP	−0.42	−0.13	−0.45	−0.06	−0.19	−0.18	0.23	0.62	1.00																										
PAW	0.13	0.45	0.48	0.14	−0.01	0.00	0.01	−0.16	−0.54	1.00																									
BD	−0.25	0.04	0.02	0.02	0.21	0.17	−0.21	0.29	−0.02	−0.13	1.00																								
WAS	−0.22	−0.10	−0.13	−0.09	−0.18	−0.34	0.37	0.24	0.53	−0.32	−0.02	1.00																							
pH	0.09	−0.41	−0.53	0.08	−0.21	0.24	−0.19	−0.15	0.15	−0.29	−0.04	−0.26	1.00																						
CEC	−0.18	0.39	0.48	−0.22	0.15	−0.30	0.26	0.21	0.11	0.24	−0.05	0.28	−0.87	1.00																					
SOM	0.02	0.28	0.30	−0.09	0.30	−0.11	0.05	0.39	0.23	0.12	0.13	0.32	−0.56	0.59	1.00																				
C	0.02	0.20	0.07	−0.12	0.22	−0.12	0.07	0.49	0.44	0.06	0.11	0.24	−0.27	0.38	0.89	1.00																			
N	−0.11	0.28	0.27	−0.15	0.37	−0.11	0.03	0.35	0.20	0.06	0.25	0.32	−0.65	0.67	0.91	0.81	1.00																		
C/N	0.18	−0.16	−0.33	0.00	−0.17	−0.05	0.09	0.29	0.47	−0.12	−0.17	−0.05	0.53	−0.36	0.07	0.43	−0.17	1.00																	
MBC	0.10	−0.08	−0.20	0.08	−0.11	0.05	−0.03	0.07	0.32	−0.22	−0.04	0.03	0.20	−0.08	0.22	0.39	0.11	0.47	1.00																
MBN	0.31	−0.15	−0.30	0.14	−0.21	−0.27	0.31	−0.06	0.13	−0.28	−0.13	0.09	0.21	−0.31	−0.13	0.00	−0.23	0.34	0.34	1.00															
NH4	−0.26	0.44	0.09	0.39	0.25	−0.30	0.24	0.12	0.07	0.00	0.10	0.17	−0.22	0.23	0.22	0.17	0.34	−0.22	−0.14	−0.17	1.00														
NO3	−0.20	0.57	0.12	0.32	0.39	−0.22	0.13	0.09	−0.13	0.30	0.01	0.00	−0.14	0.12	0.18	0.13	0.22	−0.16	−0.11	−0.09	0.65	1.00													
TIN	−0.24	0.57	0.12	0.38	0.36	−0.27	0.19	0.11	−0.05	0.19	0.05	0.07	−0.18	0.18	0.22	0.16	0.29	−0.20	−0.13	−0.13	0.86	0.95	1.00												
Pa	−0.19	0.07	0.01	0.13	−0.06	0.04	−0.03	0.18	0.22	0.14	−0.15	0.00	−0.07	0.17	0.19	0.24	0.20	0.14	0.10	−0.11	0.06	0.05	0.06	1.00											
K	−0.25	0.38	0.23	0.07	0.26	−0.20	0.15	0.19	−0.10	0.09	0.15	0.14	−0.40	0.29	0.38	0.18	0.44	−0.36	−0.19	−0.33	0.53	0.39	0.49	0.18	1.00										
Sul	0.09	0.31	0.46	0.06	0.39	0.29	−0.36	−0.18	−0.58	0.45	0.20	−0.25	−0.35	0.18	0.04	−0.12	0.16	−0.51	−0.33	−0.18	0.13	0.27	0.24	−0.17	0.21	1.00									
Ca	0.07	0.09	−0.03	−0.16	0.04	−0.33	0.31	0.24	0.58	−0.18	−0.14	0.20	−0.02	0.29	0.38	0.50	0.29	0.42	0.27	0.09	0.16	0.03	0.09	0.21	0.09	−0.38	1.00								
Mg	−0.01	−0.05	−0.23	−0.07	−0.13	−0.21	0.23	0.09	0.60	−0.22	−0.20	0.05	0.52	−0.13	−0.05	0.21	−0.13	0.58	0.27	0.09	0.05	−0.05	−0.01	0.16	−0.20	−0.54	0.72	1.00							
Na	0.18	0.01	0.28	−0.05	0.14	0.16	−0.18	−0.23	−0.39	0.35	0.14	−0.01	−0.20	0.02	−0.05	−0.20	−0.03	−0.33	−0.29	0.15	−0.14	0.10	0.01	−0.06	−0.05	0.42	−0.25	−0.33	1.00						
Bor	0.14	−0.12	−0.30	−0.08	−0.19	0.06	−0.02	−0.07	0.27	−0.05	−0.13	−0.15	0.69	−0.47	−0.24	0.05	−0.32	0.57	0.24	0.25	−0.11	−0.08	−0.10	0.03	−0.30	−0.39	0.43	0.74	−0.14	1.00					
Fe	−0.25	0.33	0.39	0.02	−0.03	−0.32	0.32	0.19	0.01	0.24	0.04	0.22	−0.79	0.68	0.50	0.29	0.49	−0.27	−0.17	0.00	0.20	0.14	0.18	0.26	0.26	0.15	0.04	−0.41	0.21	−0.55	1.00				
Mn	−0.16	0.14	0.19	0.01	−0.20	0.19	−0.15	−0.25	−0.25	0.36	0.11	−0.32	0.03	0.15	−0.34	−0.39	−0.18	−0.39	−0.15	−0.46	0.06	0.02	0.04	0.16	−0.03	0.09	−0.12	0.04	0.07	0.02	−0.10	1.00			
Cu	−0.16	0.15	−0.07	−0.03	−0.36	−0.23	0.30	0.19	0.64	−0.04	−0.17	0.18	0.13	0.18	0.11	0.30	0.04	0.45	0.23	0.13	0.09	0.02	0.05	0.41	−0.22	−0.50	0.65	0.72	−0.12	0.48	0.13	0.15	1.00		
Zn	0.13	0.10	−0.01	0.08	−0.14	0.07	−0.04	0.28	0.21	−0.03	0.02	0.13	−0.05	0.08	0.46	0.53	0.35	0.30	0.24	0.11	0.10	0.07	0.09	0.47	0.11	−0.15	0.46	0.19	−0.16	0.18	0.22	−0.10	0.42	1.00	
Al	−0.05	0.02	0.29	0.01	0.13	0.03	−0.06	−0.15	−0.49	0.20	0.09	0.01	−0.57	0.29	0.05	−0.27	0.09	−0.62	−0.42	−0.11	0.02	0.05	0.04	−0.17	0.27	0.53	−0.56	−0.83	0.41	−0.75	0.55	−0.01	−0.62	−0.30	1.00

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