Machine-Learning and Meta-Analysis Techniques to Quantify and Predict Soil Organic Carbon, N_2O-N and CO_2-C Emissions in Cover Crop Systems

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MACHINE-LEARNING AND META-ANALYSIS TECHNIQUES TO QUANTIFY AND PREDICT SOIL ORGANIC CARBON, N_2O-N AND CO_2-C EMISSIONS IN COVER CROP SYSTEMS

BY

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DISSERTATION ACCEPTANCE PAGE

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This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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My aim was to obtain a PhD degree, which is why I moved to the United States. With this degree, I am going to complete my formal education, and I would like to dedicate this degree to my main adviser, Dr. David E. Clay, my mother (Sharadha Joshi), my father (Jaya Prasad Joshi), and my wife (Prakriti Sharma). Moreover, thank you so much Dr. David E. Clay, for shaping me over the previous nine years. I am grateful, pleased, and proud to have had this life-changing experience and opportunity under your guidance and mentorship. Similarly, I'd like to thank my PhD committee members Dr. Sharon A. Clay, Dr. Thandiwe Nleya and Dr. Gary Hatfield for their years of support, ideas, and advice. In addition, I'd like to thank my coworkers Janet Miller, Graig Reicks, and Shaina Westhoff for their assistance during our collaborative efforts.

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ABSTRACT

MACHINE-LEARNING AND META-ANALYSIS TECHNIQUES TO QUANTIFY AND PREDICT SOIL ORGANIC CARBON, N_2O-N AND CO_2-C EMISSIONS IN COVER CROP SYSTEMS

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People worldwide are challenged by multiple threats including climate change, growing populations, and soil degradation. Addressing these challenges requires understanding of the local environment, farming systems and modern technologies. These technologies include new ways to process information that include artificial intelligence, machine learning and meta-analysis. Models produced using these technologies may be useful for predicting the consequences of implementing conservation practices that reduce GHG emissions as well as for determining the carbon footprint of cropping systems that include environmentally friendly conservation technologies such as growing cover crop. Therefore, our objectives of this study were to: 1) provide an overview of conservation agriculture technology as strategy to minimize soil degradation, climate change challenges, and food insecurity issues in developing countries like Nepal, 2) conduct global meta-analysis to quantify the impact of cover crops as one of conservation agriculture technique, on soil organic carbon (SOC) and crop yield in a corn (*Zea mays* L.) cropping system and 3) assess different machine learning based algorithms to predict the daily N_2O-N and CO_2-C emission from a decomposing rye (scientific name of rye) cover crop. For the first objective, historical data analysis indicated that air temperatures in Nepal have been increasing since 1901 at a rate of y 0.016 $^oC\ yr^{-1}$, whereas

precipitation has been decreasing at a rate of -0.137 mm yr^{-1}. Increasing air temperature, when combined with decreasing precipitation, are interacting to reduce crop growth and yield, diminishing Nepal's food security. We proposed conservation agriculture practices such as planting cover crop as farmer and environment friendly approach to mitigate and adopt the climate change impact and enhance food security. In second objective, I used meta- analysis approach to measure the effect of cover crop on SOC values in corn at a global scale. During the meta-analysis, data from 62 globally published peer reviewed literature showed that cover crops in the corn production system increased SOC by an average of 7.8%. The SOC increased at rates of 0.46 and 0.80 Mg/ha/year at the 0-15 and 0-30 cm soil depths respectively, due to cover crop planting. To meet the third objective, several different machine learning prediction models were tested, which included multiple linear regression (MLR), partial least square regression (PLSR), support vector machine (SVM), random forest (RF), and artificial neural network (ANN), on daily N_2O-N and CO_2-C emission data which were measured from a decomposing cover crop in 2019 and 2020 at Aurora, SD, USA. Each models' performance was accessed using coefficient of determination (R^2) (higher values close to one were deemed 'best'), root mean square error (RMSE) and mean absolute error (MAE), where lowest values were 'best'. Out of all models, the RF model accounted for 73% and 85% of the variability explained in N_2O-N and CO_2-C emissions, respectively. Across the three objectives, we found that new analysis approaches such as machine learning and meta-analysis can be used to determine the carbon footprint and prediction of GHG emission from conservation agriculture practices such as planting cover crops.

INTRODUCTION

People throughout the world are facing a variety of challenges, including climate change, expanding populations, and the degradation of the soil resources. Understanding the local environment, farming methods, and modern technologies that incorporate data science, such as artificial intelligence, machine learning, and meta-analysis, will provide more insight into targeting solutions to address these difficulties. By integrating farmer friendly conservation practices such as growing cover crops alongside modern artificial intelligence technology in agriculture decision support, can help to reduce food insecurity, climate change impact and soil degradation. Planting cover crops is a technique that can be used to reverse the impacts of agriculture on climate change. However there have been mixed findings on how the growing cover crop effects CO_2 and N_2O emissions and crop yields. Since biogeochemistry of the soil differs between the green growth and degradation (termination) phases, it is vital to study them separately to determine the net emission of a cover crop. Moreover, it is also important to develop models to more accurately predict the different greenhouse gas emissions which are needed to better understand how different agricultural practices can best be manipulated to help mitigate climate change.

Additionally, there has been many studies conducted globally about the impact of cover crops on soil organic carbon, but the findings are not consistent across production systems and climates. Thus, to obtain a comprehensive understanding of how cover crops affect carbon sequestration in different soil types, climate, cover crop types and tillage methods, and rotations a synthesis paper is needed.

To achieve the sustainable development goals of the United Nations requires innovations in agriculture and development of climate-smart and economically feasible approaches for smallholder farmers in developing countries like Nepal. Therefore, there is need to review existing literature that can provide an overview of farming practices in Nepal. It is important to highlight near-term, as well as long term, challenges associated with climate change and food security and discuss the role of conservation agriculture as a climate-smart strategy to minimize soil degradation and improve food security in such countries.

Chapter 1

Conservation Agriculture for Food Security and Climate Resilience in Nepal

Abstract

Achieving the sustainable development goals of the United Nations requires innovations in agriculture and development of climate-smart and economically feasible approaches for smallholder farmers in developing countries. Historical climate data of Nepal, which include 116 years since 1901, has shown an increasing trend for average temperature by 0.016 ^{o}C yr^{-1} whereas precipitation has shown a decreasing trend by 0.137 mm yr^{-1}. Such weather trends could enhance glacier melt associated flooding, and delayed monsoon rainfalls negatively impacting the agricultural production. The Nepalese government is promoting conservation agriculture (CA) through development of low-cost technologies that can be used effectively in difficult terrains. Such techniques include crop diversification, crop rotation, cover crops and minimum tillage, all of which can reduce soil degradation. In addition, increasing crop residue retention can result in greater C sequestration and crop yield and reductions in greenhouse gas emissions. However, there is still lack of consensus on the merits of CA in the context of smallholder farming systems in Nepal. This paper reviews existing literature and provides an overview of farming practices in Nepal, highlights near-term challenges associated with climate change and food security, and discusses the role of CA as a climate-smart strategy to minimize soil degradation and improve food security.

An overview of the Nepalese farming system

The agriculture sector of Nepal employs approximately 66% of the country's labor force, representing the main driver of economic growth and food security (Cosic et al., 2017). A typical farm has a limited land area, with the average household owning 0.68 ha of land (CBS, 2013). The country has three physiographic regions namely, Terai, Hills, and Mountains, with several agroecological niches for crop and livestock production (Figure 1. 1.). The farming practices in different agroecological zones (Figure 3.2) vary based on resource availability, land-use systems, environment, farming activities, productivity, and access to utilities such as road and market networks.

The Terai plains lie at the lowest altitude (<1000 m.a.s.l) and support 20% of agricultural land (Paudel et al., 2009). The Koppen climate zone of this region is Tropical Savannah (Aw) (Karki et al., 2016) and is conducive to growing up to three crops, rice (*Oryza sativa* L.) -wheat (*Triticum aestivum*)-rice, rice-wheat, rice-maize (*Zea mays* L.), a year if irrigation facilities are present (Table 1.1). This region receives 80% of the annual rainfall during summer monsoon season (June to September) whereas the winter season is dry. Due to fertile soils, favorable climatic conditions, easy access to irrigation and chemical fertilizers and pesticides, crop yields are greatest in the Terai than in any other region (MOAC, 2010; Shresth et al., 2013). For example, in Peri-urban areas near the capital city Kathmandu, use of the pesticides has increased by 30% in 2015 compared with 2014 especially for vegetable production, due to easy access and better infrastructure (Jeranyama et al., 2020). In the irrigated cropping systems in the Terai and lower hill valleys, rice and wheat are predominant as summer and winter cereal crops, respectively, whereas in the upland non-irrigated region, the main crop is maize.

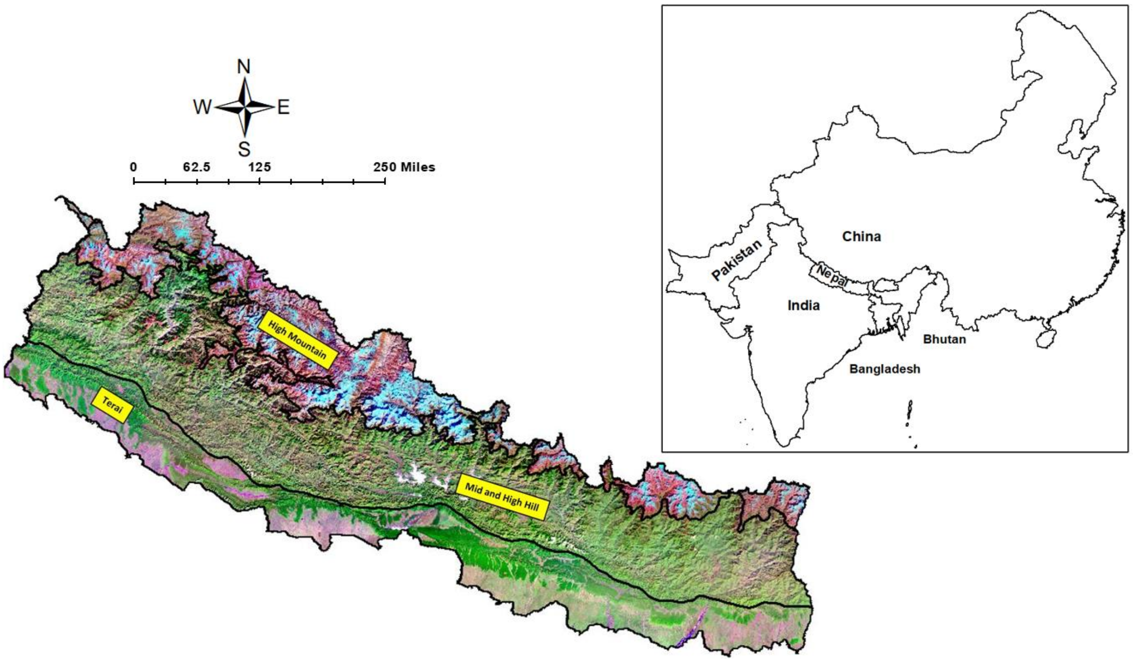

Figure 1. 1. Terai, Hill, and Mountain Eco-Regions of Nepal. (Raw data source: MoALC, 2018; ESA, 2021)

Hills and Mountain terrains represent 80% of Nepal's agricultural area (Paudel et al., 2009). Based on Koppen climate classification, hill region is Cwa (Temperate Climate with dry winter and hot summer) , Cwb (Temperate Climatewith dry winter and warm summer) and Dwb (Cold Climate with Dry winter and warm summer), whereas the high mountain regions have ET (Polar Tundra) and EF (Polar frost) climate. Crop yields in the hills and mountains are often low due to the small size of fields in the terraced land, rainfed agriculture, and difficulty accessing input supplies due to lack of adequate roads and markets (Ghimire et al., 2020). In the hill region, maize is rotated with other cereal crops (Table 1.1). Upland rice, tea (*Camellia sinensis* L. Kuntze), cardamom (*Elettaria cardamomum* L. Maton), ginger (*Zingiber officinale* Roscoe), and coffee (*Coffea arabica* L.) are also cultivated in the areas where soil and climate are favorable. In the mountains, crops like buckwheat (*Fagopyrum esculentum*) and naked barley (*Hordeum vulgare* L. ssp. vulgare) are cultivated in some areas. In addition, the pastoral system of livestock grazing is also combined with crop production in high mountain locations due to rough terrain and short growing season.

Table 1. 1. Major cropping systems in different ecological zones of Nepal.

Terai and lower mountain valley (<1000 m.a.s.l)	Middle mountain (1000-2000 m.a.s.l)	High mountains (2000-3000 m.a.s.l)
Rice-wheat	Rice-wheat	Maize -finger millet (*Eleusine coracana* L. Gaertn).
Rice-rice	Rice-winter legumes	Maize-wheat/barley
Rice-wheat-maize	Maize-wheat	Maize-buckwheat
Rice-vegetable	Maize-winter legumes	Buckwheat-fallow
Rice-wheat-vegetable	Maize-vegetables	Potato (*Solanum tuberosum* L.)-fallow

(Source: modified from Ghimire et al., 2020)

Figure 1. 2. Typical farming systems in Terai (a), Hill (b) and Mountain (c) regions of Nepal. (Source: Rajan Ghimire, Ecological Services Center, Nepal).

The livestock sector contributes a major part to sustainable agriculture and the rural economy. Grain cultivation and livestock production are complementary, and for the most part, households combine the production of subsistence crops with small numbers of livestock as mixed farming systems. Large ruminant animals such as buffalo (*Bubalus bubalis*) bulls and oxen (*Bos taurus*) provide farm power in most areas. Overall, the livestock sector contributes about 26% of the agricultural economy in the country (MOAD, 2017). On the other hand, using animal power for different agricultural operations, is time consuming and labor intensive. The introduction of mini-tillers and hand tractors for field operations under the Prime Minister Agricultural Modernization project (a 10-yr project which began in 2016) has shifted the role of livestock from a major source of draught animal power and manure contributor to mostly a source of protein (milk and meat) and manure for crop production (PMAMP, 2021). It is reported that planting potatoes on a katha (about 0.3 ha) of land by traditional means used to take a day, but using mechanized equipment takes about 20 minutes. This may potentially change agricultural practices for the Nepalese farmers.

Challenges for food security in Nepal

The agriculture sector in Nepal faces challenges due to its unique topography and physiography of the country (Figure 1.2). About 60% of the farmers surveyed across the country reported they are not able to sustain their livelihood from agricultural production alone due to low crop productivity (CBS, 2011). Although the production trend has been increasing over the decades, it is not adequate to meet the demand of the increasing population (FAO, 2015). Mostly, the farmers in hill regions of western Nepal face food deficit conditions due to the fragile landscape, lack of access to resources, and lack of inputs and training on improved farming practices (such as quality seed, adequate fertilization, crop rotation). The food shortage situation is increasing as a result of many environmental effects induced by conventional agriculture practices. For example, many studies report a significant amount of soil loss from conventional agricultural fields (Chalise et al., 2020; Kiboi et al., 2017; Koirala et al., 2019; Shao et al., 2016). The soil erosion rate is estimated at 1.7 mm (about 22 Mg ha^{-1}) of topsoil each year in Nepal (Chalise et al., 2019). In another study using Revised Universal Soil Loss Equation (RUSLE) model combined with a geospatial tool reported annual soil erosion of 35, 18, and 0.1 Mg ha^{-1} in Mountain, Mid-Hills and Terai, respectively (Koirala et al., 2019). Such soil losses from erosion reduce the organic matter, N, P and K content of the land and ultimately affects the soil nutrient status and reduces the crop yield (Tiwari et al., 2010).

Climate change exhibits an additional threat to food security in Nepal. Warmer temperatures and lower rainfall results in less water in dams for irrigation which then reduces the potential to maintain food production and crop yields. From 1977 to 2009, there was a record average 0.06 ^{o}C increase in average annual temperature, which shows a warming trend over the years (Shrestha et al., 2011). The models developed to assess temperature rise over time in Nepal predict an increase of 1.2 ^{O}C by 2030 (WWF, 2005). The global circulation models (GCM) predict that the number of extremely hot days per annum will increase by 55% by the 2060s and by 70% in the 2090s (NCVST, 2009). Similarly, using the 116 years of historical data for Nepal, temperature anomalies revealed inter-annual fluctuations and temperature change patterns have increased over the long-term. The rate of change was determined from the slope of the linear regression model, which was 0.016 ^{o}C $year^{-1}$ (Figure 3.3.a). This increasing trend was even faster after 1975, with an annual increase rate of 0.035 ^{o} C $year^{-1}$. In the case of precipitation, however, historical data showed a declining trend at the rate of -0.137 mm $year^{-1}$ (Figure

1.3.b). After 1975, the precipitation decline rate was -0.255 mm year^{-1}. These results indicate the climate change impacts have been more severe during the last 41 years from 1975 to 2016.

The issue of food security has become a greater problem with the severe climate change impacts over the last few decades. According to the IPCC fifth assessment, climate change has negatively impacted crop production in many regions of the world (IPCC, 2014). Several studies have reported decreased yield with increased temperature in most crops (Challinor et al., 2014; Lobell and Field, 2007; Sarker et al., 2014; Jiang et al., 2020). The resultant risk of crop failure and volatility of food supply is much higher for subsistence farmers due to sole dependence on agriculture, poor production environment, and lack of knowledge and innovation for adaptive techniques to cope with extreme environmental conditions (Aryal et al., 2019, Islam et al., 2016, Hussain et al., 2016). Studies on the Hindukush Himalayan region, including Nepal and south Asian countries, have reported unprecedented trends in precipitation patterns and hydrological imbalances, increases in temperature and recurring floods, and the deterioration of forests, rangelands, and agricultural lands (Gentle & Maraseni 2012; Gawith et al., 2015; Hussain et al., 2016). In a country where almost two-thirds of agricultural land is rainfed, crop production is more vulnerable to high temperatures and seasonal rainfall (Gentle & Maraseni 2012).

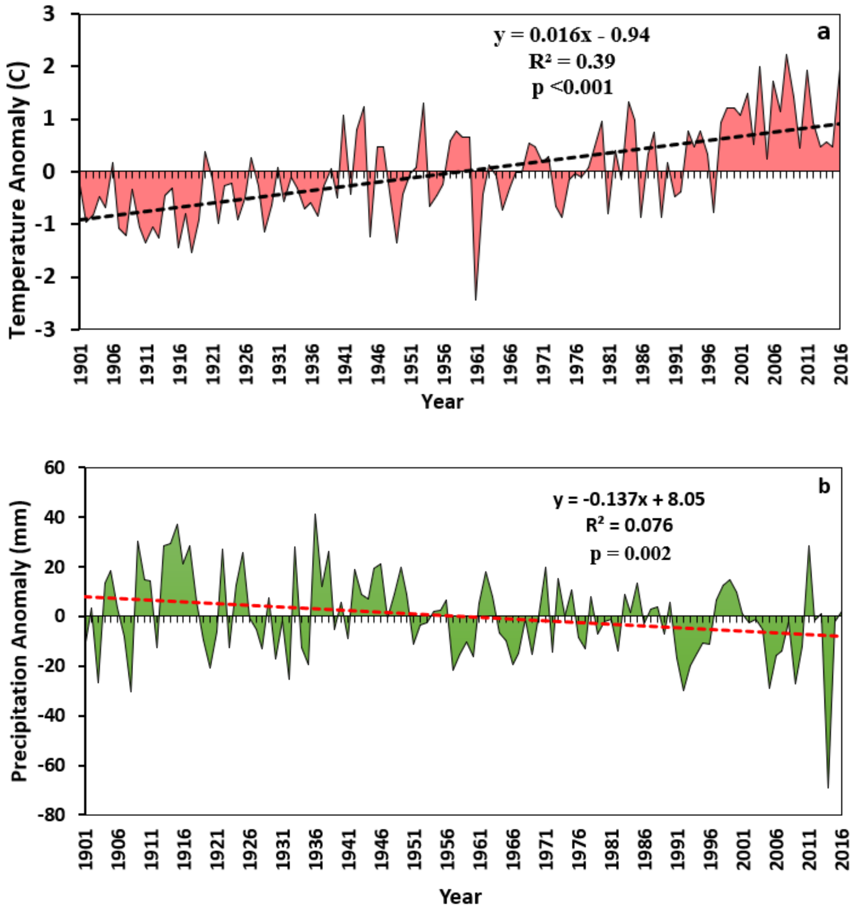

Figure 1. 3.Temperature (a) and precipitation (b) change in Nepal from 1901 to 2016. Over the 116-year period, while highly fluctuating, there are trends for higher annual temperature and lower precipitation. Graph area above zero indicate increases whereas areas below zero indicate decreasing trend. The average from 1901 to 2016 was used as a benchmark for representing change in this graph. (Raw data source: World Bank Climate Change Knowledge Portal, 2021)

The climate change impact in Nepalese agriculture has resulted in severe natural calamities such as frequent drought and floods, landslides, and diminishing productivity of agricultural crops (Malla, 2008). The effect of temperature rise is directly related to productivity loss as heat waves affect the physiology of plants (Rasul et al., 2011). Increased variability in temperature and more frequent occurrence of extreme weather events has increased the vulnerability of crops to biotic and abiotic stresses (Hansen et al., 2013) and altered the timing of agricultural operations, affecting crop production

(Paudel et al., 2014a). Increasing trend of temperature is expected to reduce the wheat and maize yields (Bhatt et al., 2014). Specifically, frequent droughts during winter are expected to reduce winter crop production. This leads to further depletion of water resources like rivers and dams which leads to immense challenges in irrigated agriculture production potential across the country.

Conservation agriculture is a climate-smart solution for food security

Conservation Agriculture (CA) practices (Figure 1.4.) can improve food security, prevent land degradation, and improve the resilience of cropping systems against climate change in Nepal, irrespective of climatic zones and physiographic differences. Food production on degraded soils without adopting proper management practices does not necessarily decrease food security; instead, it increases environmental problems (Clay et al., 2014 ; Joshi et al., 2019). Nepalese agriculture consists of predominantly Mountain agriculture, with 56.8% agricultural land (Paudel et al., 2017) in sloping or terrace landscapes which have low fertility, coarse-textured soil, heavy cracking clays, or other problems (Shahid & Al-Shankiti, 2013). Sustainable food production in such land under the new realities of climate change can only be successful with holistic approaches that include all possible aspects of soil, water, and crop management. Sustainable agriculture and environment can be ensured in the mountainous landscapes by following the main principles of CA such as 1) ensure adequate living and residual biomass to improve soil and water conservation and control soil erosion, the preservation of permanent soil cover, and the promotion of minimal mechanical disruption of soil through no-tillage systems, 2) support good, living soil by rotating crops, cover crops and using integrated technologies for the management of pests, and 3) promote legume crops, agroforestry, and diversified cropping systems (Dumanski et al., 2006). Adoption of these principles in mountain farming could provide climate-smart solutions to improve food security through their positive effects on soil carbon sequestration, greenhouse gas mitigation, improved nutrient cycling, and agrobiodiversity (Figure 1.4.).

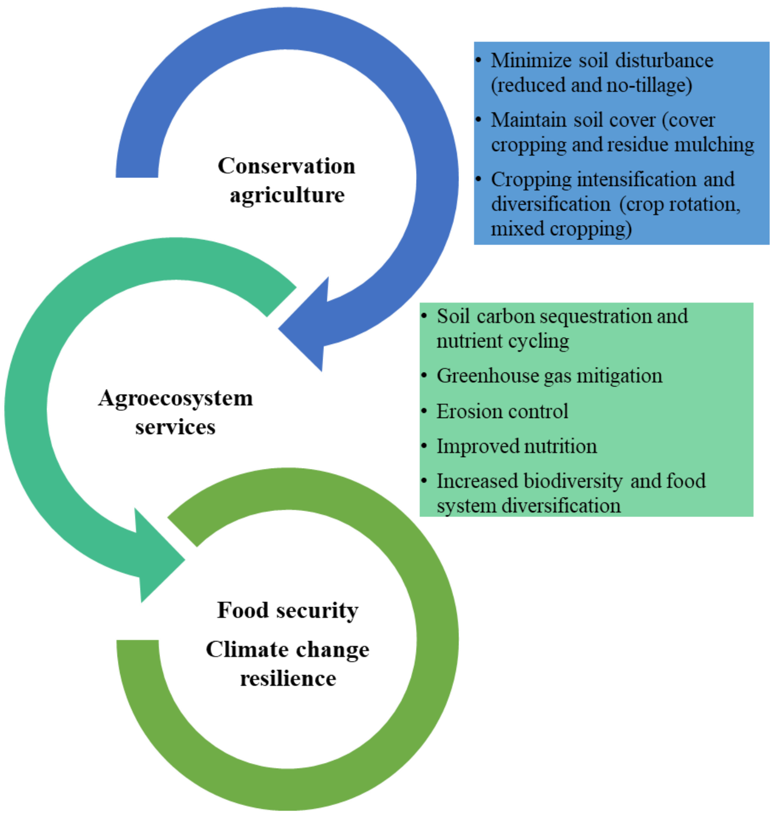

Figure 1. 4. A conceptual model for increasing food security and climate resilience in agriculture through conservation agriculture.

Conservation Agriculture minimizes soil disturbance, provides crop residue coverage, and diversifies and intensifies cropping systems, and minimizes soil degradation due to excessive chemical fertilizer application, low organic matter input, monoculture, and conventional tillage (García-Torres et al., 2001). In fragile sloping lands of hills and mountains, vegetation on field boundaries is practiced to reduce soil erosion (Brown and Shrestha, 2000; Dougill et al., 2001; Matthews and Pilbeam, 2005).

The benefits of CA practices have been documented in the Terai rice-wheat systems and integrated farming in Mid Hill region of Nepal (Table 1.2.). For example, no-tillage alone could sequester 140 kg soil organic carbon (SOC) ha^{-1} y^{-1}, while no-tillage with residue addition could increase SOC by up to 480 kg ha^{-1} y^{-1} (Ghimire et al., 2012). No-till management has increased crop production in an environmentally and socially sustainable manner, and cover crops can reduce greenhouse gas emissions (Reicks et al., 2021) and increase the carbon sequestration on agricultural land (Schwab et al., 2015; Jat et al., 2020). In a meta-analysis of CA practices in South Asia, no-tillage with residue retention increased crop yields by 5.8%, water use efficiency by 12.6%, net economic return by 25.9%, and reduced greenhouse gas emissions by 12–33%, with more-favorable responses on loamy soils and in maize–wheat systems (Jat et al., 2020).

Table 1. 2. Effects of alternative management on soil organic carbon under various crops and cropping systems in Terai and Mid Hill region of Nepal.

Zone	Soil type	Cropping system	Depth (cm)	Year	Typical practice	CA tools	% SOC increase	Reference
Mid Hill	Sandy Loam	Integrated farming	15	3	Traditional FYM management	SSM of FYM	13.55	Bishwakarma et al. 2015
Terai	Sandy Loam	R-W	20	2	CT	NT, crop residue	16.83	Paudel et al. 2014b
Terai	Sandy clay loam	R-W	50	3.5	CT	NT	9.89	Ghimire et al. 2012
Terai	Silty loam	R-R-W	12	20	N fertilizer	N + FYM	12.98	Regmi et al. 2002
Terai	Sandy	R-W-	20	20	NF	FYM, crop residue	62	Gami et al. 2001

[1]FYM, Farmyard manure; SSM, Sustainable Soil Management; NPK, Nitrogen-Phosphorus-Potassium; CT, Conventional tillage; NF, No fertilizer; NT, No- till; R-W, Rice-wheat; R-R-W, Rice-rice-wheat

The CA techniques of no-till and use of mulch and cover cropping can reduce soil erosion (Clay et al., 2014; Seitz et al., 2018), improve soil aggregate structure, support microbial growth, increase soil organic matter, and reduce soil erosion (Ghabbour et al., 2017; Mikha and Rice, 2004; Six et al., 2000). Through the integrated management of soil, water, and biological resources, CA reduces external inputs and improves farmers' independence (Figure 1.4.). Maintaining a permanent or semi-permanent soil cover, whether a live crop or dead litter, which protects the soil from the sun, rain, and wind, and supports biological activities (Joshi et al., 2020), is the primary and, indeed, the central tenet of CA. Adopting conservation buffer systems in the mountains and hills of Nepal has reduced soil erosion and improved overall farming system performance (Schwab et al., 2015). Studies find higher microbial biomass with residue retention than with removal (Palm et al., 2014), with no-tillage rather than conventional tillage, and with crop rotation compared to monocropping (Clay et al., 2014).

Despite all the benefits of CA on the environment and sustainability, yield benefits are not universal. Laborde et al. (2019), Pittelkow et al. (2015), and Rusinamhodzi et al. (2011) reported that CA had less yield benefit as compared to the conventional system. Some studies report no change or little change in the yields, especially in the early years of the CA system's implementation (Ghimire & Bista, 2016; Laborde et al., 2019), while many other studies show considerably higher yields with CA than the conventional system (Kodzwa et al., 2020; TerAvest et al., 2019). More studies in the hills and mountains of Nepal will reveal the benefits of CA on region-specific farming systems, but overall positive effects of CA have been documented for South Asia. In a meta-analysis evaluating various combinations of CA practices in South Asia, Jat et al. (2020) reported significant positive effects of no-tillage and residue retention on crop yields and economic return. Their findings of 20- 41% higher economic return and 12–33% reduction in global warming potential with the adoption of CA practices show significant positive effects of CA on food security and climate change mitigation.

Policy recommendations

Despite the country’s effort on agricultural modernization by implementing various agricultural plans and policies such as Agriculture Perspective Plan (1995), the National Agriculture Policy (2004) and Three-Year Interim Plan (2007/08–2009/10), agricultural transformation, and food security status in Nepal has lagged behind many other countries. Sustainable intensification is a major challenge in mountain agriculture across the world since mountain ecosystems are largely associated with lower soil fertility, increased soil erosion and reduced biodiversity (Schwab et al., 2015). Different policies and programs are required to encourage the use of CA-methods. For example, more investment on rural road building, specifically in hills and mountain, may assist farmers in moving machinery and equipment. Also, by improving farmers' mechanization capacity, and providing irrigation facilities to rainfed areas, adoption of CA could be increased. Furthermore, there is a lack of farm-level access to technology and information in rural areas. As a result, strong extension and research ties through government agencies may assist farmers become more aware of the benefits of CA. More investment in research, outreach and technology development in hills and mountain regions could boost agricultural production in these areas and enhance food security status of the country. The government sector has recently taken a number of steps. For instance, in 2016 10-yr initiative, the Prime Minister Agricultural Modernization Project of the federal government, the Climate-Smart Village program of the Provincial governments and other sustainable agriculture programs have begun to address climate change and other challenges in agriculture through integrated approaches in crop and livestock management. Agricultural mechanization, region-specific commodity crop production, cooperative farming, and identification of niche markets are prioritized under this program to increase agricultural production and support the smallholder-farm economy (PMAMP, 2021).

Conclusions

The CA involves a combination of production technologies to attain high yield on existing land to meet the domestic and global food demands with minimal environmental impacts. Evaluation of various aspects of CA revealed benefits by minimizing soil disturbance, soil erosion, and pest pressure, and by increasing SOM and aggregate stability. These effects are more pronounced in degraded soils. The benefits of CA documented from Nepal has shown promise especially in the mountain agroecosystem which faces sustainability challenges due to steep and fragile topography and rapid climate change. Implementing region-specific CA adaptation strategies and working closely with farmers to identify a suitable conservation tool will minimize climate change-associated risk and uncertainties in food production. Some model assessment suggests an increased yield of selected crops with a moderate rise in temperature and increased precipitation. Identifying those crops and developing a conservation management strategy will address both challenges, food security and climate change.

Even with all the advantages, there are still many challenges to CA adoption in Nepal, where the majority of farmers lack financial capital, and continue to practice traditional subsistence farming on small field parcels. Resource-poor farmers cannot easily cope with associated yield loss during the early years of transition to CA practice (Rapsomanikis, 2015). Thus, governmental policies are needed to support farmers and provide economic incentives through crop insurance or subsidies in the agricultural inputs, at least during the initial years of the CA practicing. The government needs to prioritize and promote low-cost technologies that can be used effectively in difficult terrains.

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Chapter 2

A Global Meta-analysis of Cover Crop Response on Soil Carbon Storage Within a Corn Production System.

Abstract

In agriculture, photosynthesis converts atmospheric CO_2 to organic carbon in plants (fixation), which is eventually oxidized to CO_2 through respiration. If carbon fixation is greater than respiration, then soil organic C (SOC) levels can increase. This meta-analysis evaluated the effect of cover crop in rotations that include corn (*Zea mays*) on SOC. Information on climatic conditions, soil characteristics, and management was extracted from 315 paired comparisons contained in 62 peer- reviewed cover crop studies. Overall, cover crops grown in corn rotations increased SOC by 7.8% (ranged from 5.4 to 10.8%). The SOC increase was attributed to CO_2 fixation by the cover crop being greater than the amount of SOC lost through respiration. Our findings showed that SOC storage in no-tillage systems was increased by 8.5% (ranged from 5.9 to 11.9%) whereas SOC stored in tilled systems was increased by 6.6% (ranged from 3.6 to 10.2%). In a corn following corn rotation, SOC storage was increased by 8.6% (ranged from 5.1 to 12.9%), whereas in a corn following soybean (*Glycine max*) rotation SOC storage increased by 5.1% (ranged from 1.1 to 9.5%). These data suggest that current cover crops/corn production systems are sequestering 5.0 million Mg of SOC-C year^{-1} in the United States and has potential to sequester 160 million Mg SOC year^{-1} globally. Along with increasing SOC, adopting cover crops increased corn yield by 23.0% (ranged from 4.8 to 52.7%). These findings can be used to improve carbon footprint calculations and develop science-based policy recommendations.

Introduction

In 2020, 1162 million metric tons of corn grain were produced globally on 202 million hectares of land (FAOSTAT., 2022). Corn grain is used to produce many products including human food, animal feed, energy products, plastics, cosmetics, diapers, and baby powder (Erenstein et al., 2021; Grote et al., 2021). Because the production of these products may increase greenhouse gas emissions (GHG), it is important to reduce the corn carbon footprint (Lee et al., 2021). It has been hypothesized that the carbon footprint can be reduced by growing cover crops within the corn production system.

Cover crops are plants that are not intended to be harvested and are used to reduce erosion by covering the soil between two cash crops. Farmers have many management options when growing cover crops including what, when, and where to plant (Reese et al., 2014). Interactions among management, climate, and soil conditions can result in cover crops having a mixed impact on cash crop yield and the carbon dioxide equivalence (CO_{2e}) (Abdalla et al., 2019; Jian et al., 2020; McClelland et al., 2021; Poeplau and Don, 2015; Joshi et al., 2022). For example, in arid and semi-arid climates, water used by the cover crop can reduce cash crop yields, whereas in temperate environments cover crops can improve soil and plant health (Reese et al., 2014).

The CO_{2e} is used to reduce the complexity of greenhouse gas (GHG) emissions from multiple gases into a single value (Joshi et al., 2022). In crop production, the dominant GHG considered in CO_{2e} calculations are N_2O, CO_2, and CH_4. This paper considers only one of those gases, CO_2. Carbon dioxide emissions can be assessed by several approaches including direct emission measurement, or by quantifying SOC spatial and temporal changes in the soil, or by some combination of both (Joshi et al., 2022). This meta-analysis is based on the reported temporal SOC changes in field experiments that contained cover crop and no cover crop treatments.

Cover crops can have a mixed impact on the amount of carbon sequestered in the soil (Blanco-Canqui, 2022). Blanco-Canqui (2022) assessment of U.S. studies considered location, annual precipitation, annual temperature, soil texture, initial SOC, tillage, cover crop species, experiment duration, cover crop biomass produced, sampling depth, and SOC stocks. In their data set, cover crops did not increase SOC in 71% of the studies. Blanco-Canqui (2022) attributed the lack of SOC increase to many factors including tillage, species, fertilization, irrigation, initial SOC, soil texture, and climate. Blanco-Canqui (2022) analysis did not provide details on how the interactions among these factors resulted in nonsignificant SOC grains in 71% of the comparisons. The lack of differences also could not be answered by Abdalla et al. (2019), Jian et al., (2020), McClelland et al. (2021), and Poeplau and Don (2015) because they failed to consider specific crops or rotations. In comparison to Blanco-Canqui (2022), our analysis narrowed the question from a wide range of crop rotations to rotations that included corn and expanded the analysis from only US studies to a worldwide analysis. Until now, there has been no such synthetic study carried out, particularly one that focuses on the corn cropping system. Thus, to provide needed information for one of world’s most widely grown crop, a synthesis paper on influence of cover crops on SOC in corn cropping system is needed. Therefore, the objectives of this paper were to conduct a global comprehensive assessment of published existing peer-reviewed literature, quantify the impact of cover crops on SOC having corn in rotation as primary focus, and to determine effect of tillage, crop rotation, cover crop types, soil texture, climate and geographic location on SOC change due to cover crops.

Materials and Methods

Literature search

This meta-analysis was conducted by searching for digital on-line peer-reviewed articles that were published until May 2022 (Figure 1). In a search of the Web of Science and google scholar, relevant articles were collected then data was extracted followed by data quality assessment and statistical analysis and interpretation (Charles et al., 2017). The key words used in the Web of Science and google scholar search were soil organic matter, soil organic carbon, soil carbon, soil C, corn, maize, *Zea mays*, cover crop, green manure, rye, oat, vetch, and catch crop. This search resulted into 3856 published articles, of which only papers published between 1990 and 2022 were considered. In addition to publication date, the articles had to meet the following criteria that included: 1) corn had to be included in the rotation; 2) changes in soil organic carbon (SOC) had to be reported; 3) the study had to contain cover crop and no cover crop treatments; 4) the cover crop was not harvested, but was terminated or incorporated, and 5) the replicated field experiment had to be completed for at least two years. Because many studies were missing critical information that could not be obtained elsewhere, only 62 were selected for data extraction (supplemental Table 1). Information on crop rotation, tillage type, cover crop type and biomass produced, method and timing of cover crop termination, fertilizer application, crop yield, location (latitude and longitude), annual temperature and precipitation, soil organic carbon (SOC) and depth of sampling, soil pH, texture, bulk density (bd), when the study was initiated and completed, number of replications, and irrigation was extracted. Whenever total carbon in soil was reported as soil organic matter (SOM), it was converted to soil organic carbon by assuming that organic matter contained 58% carbon.

Bulk density (bd) was used in the correlation and model building, as well as to convert gravimetric values to volumetric amounts using the following equations,

$$\text{SOC (Mg ha}^{-1}) = \text{SOC (\%)} \times \text{soil increment (cm)} \times \text{bd (g cm}^{-3}) \quad (1)$$

$$\text{SOC (Mg ha}^{-1}) = \text{SOC (g kg}^{-1}) \times \text{soil increment (cm)} \times \text{bd (g cm}^{-3}) \times 0.1 \quad (2)$$

Questions and gaps in the data bases were filled by contacting the authors, extracting soils information from the Web Soil Survey for U.S. studies and ISRIC SoilGrids for non-U.S. studies. Missing climate information was obtained from NOAA (NOAA, 2022). Where possible, soils information was standardized to 4 soil depths (0 -15, 0 – 30 and 0 – 60 cm).

Unless stated, it was assumed that that initial SOC values for the cover crop and no cover treatments were identical. Whenever there was difference in the initial SOC values between treatments, we either added or subtracted the difference in the final SOC as explained by Xu et al. (2019). Moreover, the soil depths were standardized to the 0 - 15, 0 - 30, and 0 - 60 cm depths. If the studies depths did not align with these categories, the method suggested by Xu et al. (2019) was followed. Using this method, adjustment was based on tillage and soil depth. For example, to convert sampling that was conducted for the 0 - 20 cm to 0 - 30 cm, the method used by Puget and Lal, (2005), Xu et al. (2019) and Yang and Wander (1999) was followed. This method was based on the vertical distribution of SOC in the soil with the assumption that SOC distribution is same throughout 0-30cm soil depth due to mixing of soil during tillage. When study used no tillage system, SOC at0-20cm depth was converted to 0-30 cm using the conversion factor of 1.35 based on vertical distribution of SOC (Puget and Lal., 2005; Xu et al., & Yang and Wander, 1999).

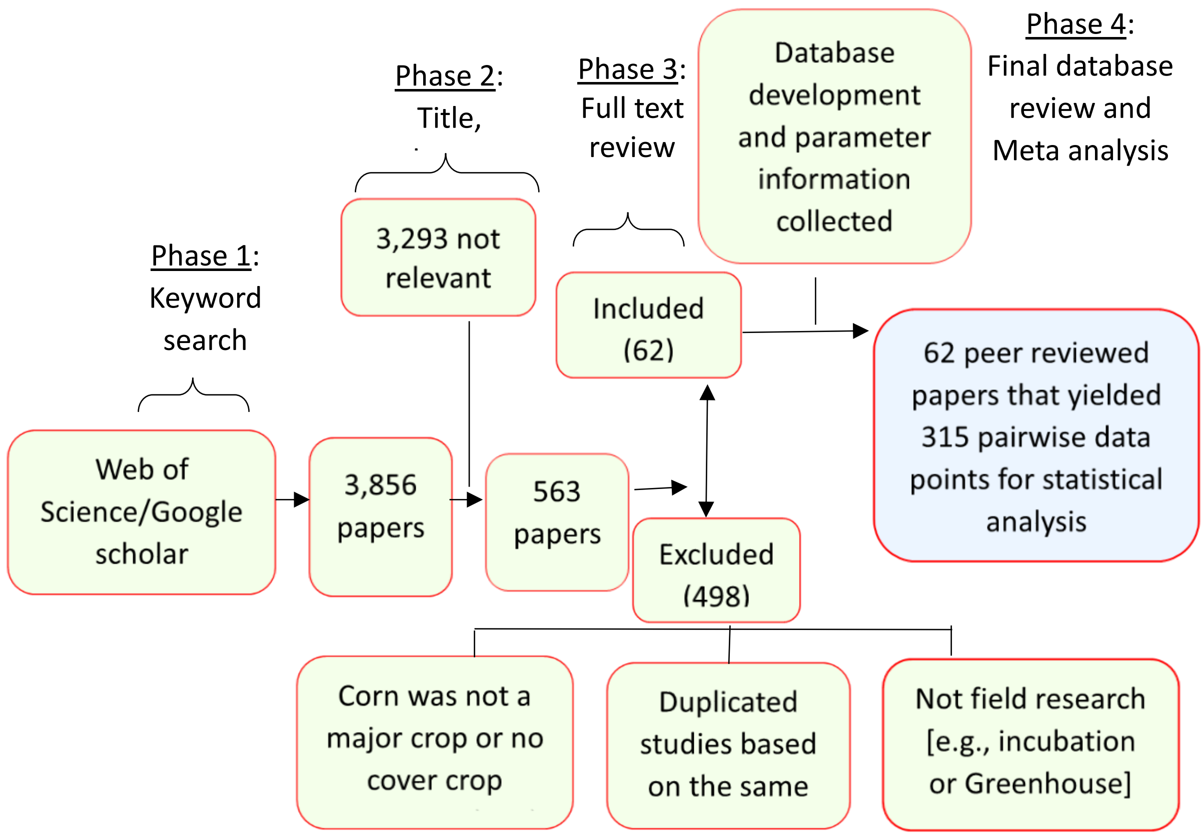


Figure 2. 1. Workflow diagram for peer-reviewed papers selection during meta-analysis.

Statistical analysis

The statistical analysis was separated into multiple categories that included exploratory data analysis, cumulative meta-analysis and sensitivity/publication bias analysis, and correlation and model building. In exploratory data analysis, the distribution of the study sites was explored using an appropriate geographic information system (GIS). In addition, the type and amount of information collected was determined using frequency plots.

Cumulative meta-analysis

The cumulative meta-analysis determined the effect of the treatments (effect size) on the measured parameters. In this analysis, the response ratio was calculated using the equation,

$$\ln(R) = \ln(\overline{X}_{CC}/\overline{X}_{NCC}) = \ln(\overline{X}_{CC}) - \ln(\overline{X}_{NCC}) \quad (3)$$

where, ln(R) was the natural log of response rations, $\overline{X}_{CC}$ was the mean SOC or yield values for the cover crop treatment, and $\overline{X}_{NCC}$ was the mean SOC or yield value for the no cover crop treatment (Hedges et al., 1999). A multilevel mixed effects meta-analytic model utilizing the "nlme" package in R (R Core Team 2017) was developed to account for multiple types of dependency between effect sizes within and across studies. Dependency was considered when the same control was used to compare several cover crop treatments within a study, as well as when multiple experiments were done at the same experimental location (Thapa et al., 2018b; Pinheiro et al., 2017; Van den Noortgate et al.,2013).

Individual impact estimates are generally weighted by the inverse of sample variances to increase the weights of studies with lower variances (Philibert et al., 2012). However, many studies did not report the standard deviation, standard errors, or coefficient of variability of the measured values. Therefore, weighting factors for the i^{th} observation (wi) were determined based on Adams et al. (1997). The weighting factor was determined with the equation,

$$w_i = (N_{CC} N_{NCC})/ (N_{CC} + N_{NCC}) \tag{4}$$

where N_{CC} and N_{NCC} were the number of replications for the cover crop and no cover crop treatments, respectively. In the end, we estimated the robust standard error for the mean effect size by utilizing the "clubSandwich" package which is cluster-based technique for robust variance estimation (Pustejovsy et al., 2022; Thapa et al., 2018a). The 95 percent confidence interval (CI) was calculated for the weighted natural log means [ln(R)]. The change in the response was determined using the equation,

$$\% \text{ change in response} = [\ e^{\ln(R)} - 1] \times 100\ \% \tag{5}$$

where ln(R) was defined in equation 3. If the 95 percent confidence interval did not contain zero, the response variable was statistically different from the controls ($p < 0.05$). The rate of change in SOC-C [Mg SOC-C $(\text{ha} \times \text{year})^{-1}$] was determined with the equation,

$$SOC\text{-}C_{rate} = (SOC_{cc,\ T1} - SOC_{cc,\ T0})/\ T \tag{6}$$

where $SOC_{cc,\ T1}$ and $SOC_{cc,\ T0}$ refer to the final (T1) and initial (TO) SOC values for the cover crop treatment and T is duration of study in years.

To study the effect of the different moderators on the cover crop SOC responses, the meta data was grouped into the following categories:

1. The amount of cover crop produced (≤ 3, 3-7 and ≥ 7 Mg biomass ha^{-1}),
2. The tillage type (cultivated [CT] and no-tillage [NT]),
3. Crop rotation types [corn-corn, corn-soybean, and corn- other]. Here corn-other includes corn rotation with any other crops such as rice (*Oryza sativa*), sunflower (*Helianthus annuus L.*), groundnut (*Arachis hypogaea*), tomato (*Solanum lycopersicum*) etc.

4. The cover crop type (legume, non-legume, and mixed). The most common legume cover crops were: Hairy vetch [*Vicia villosa*], lupin [*Lupinus polyphyllus*], Mucuna [*Mucuna pruriens*], Sesbania [*Sesbania sesban*] and mungbean [*Vigna radiata*]. The most common non-legumes were cereal rye [*Secale cereale*], canola [*Brassica napus*], radish [*Raphanus sativus*], oat [*Avena sativa*]. Cover crop mixtures of two or more species for example cereal rye + hairy vetch, winter lentil [*Lens culinaris*] + wheatgrass [*Triticum*], oat + hairy vetch.
5. The soil textures at the study site. These textures were fine (clay, silty clay loam, clay loam), medium (silt loam and loam), and coarse (sandy loam and sandy clay).
6. The Köppen climate zone of the study sites were considered and classified into tropical, temperate, and cold categories. The tropical region included: Af [tropical rainforest climate], Aw [tropical wet and dry climate], BSh [hot semi-arid climate], BSk [cold semi-arid climate] and BWh [hot desert climate] Koppen climate zones. The temperate region included Cfa [humid subtropical climate], Csa [hot summer Mediterranean climate], Cfb [temperate oceanic climate], Csb [warm summer Mediterranean climate], Cwa [monsoon subtropical climate] and Cwb [subtropical highland climate] and lastly the cold climatic region included Dfa [hot summer humid continental climate], Dfb [warm summer humid continental climate] and Dwa [monsoon influenced hot summer humid continental climate] Köppen climate zones. Most of the U.S. studies were grouped into the temperate and cold zones.

2.2.2 Publication and sensitivity analysis

The publication bias and sensitivity analysis are classically conducted using a funnel plot analysis, but many studies did not provide sample variance information, so this analysis was not conducted. To check the distribution of the dataset, a histogram was used. The histogram showed that the observations were slightly skewed (Figure 2a), and that the meta-analysis was not subject to publication bias (Basche and DeLonge, 2017; Gurevitch et al., 2001; Thapa et al., 2018a). This analysis was expanded by conducting a *Jacknife* sensitivity analysis (Philibert et al., 2012; Thapa et al., 2018a). During *Jacknife* analysis, each study was assigned a unique ID and data from one of the studies was excluded from database in each calculation. This analysis showed that no one study appeared to have a disproportionate impact on the results and that the meta-analysis was robust (Figure 2b).

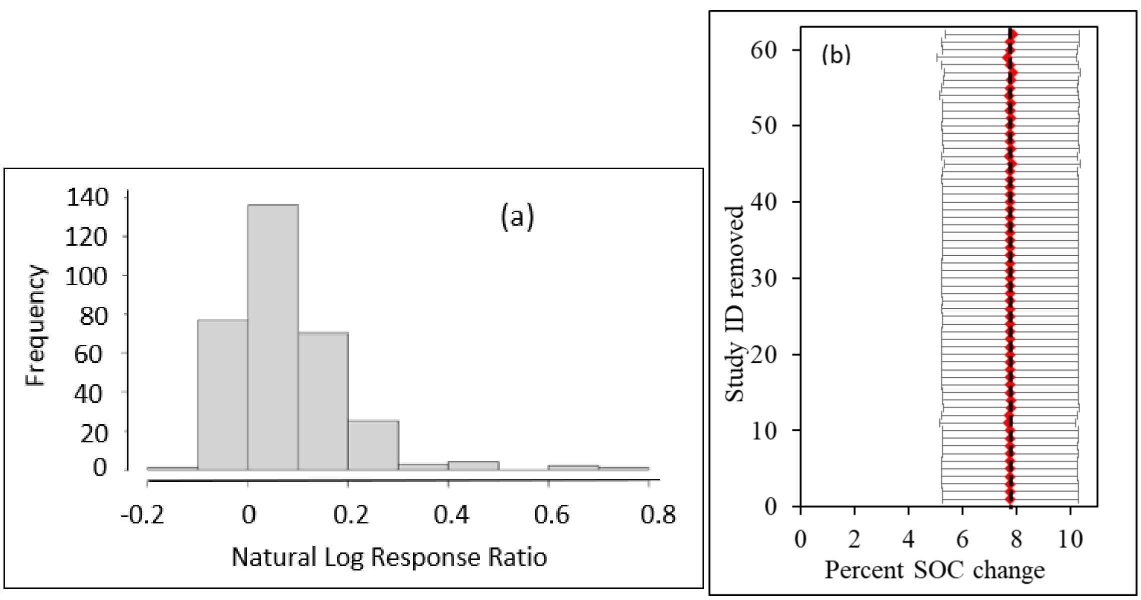


Figure 2. 2. Histogram (a) of the individual effect sizes for SOC across 315 observations. The result suggest that the individual effect sizes were normally distributed. The analysis showed that there was an absence of publication bias. Sensitivity analysis (b) was conducting using the *Jacknife* technique. The overall percent change in SOC is shown by the dashed black line. The removal of any single study had no effect on the results. This analysis showed that the meta-overall analyses were robust.

Stepwise multiple linear regression

Stepwise regression involves recursively adding and removing predictors in the predictive model to find a subset of variables that provides the best precision and accuracy. A combination of forward and backward regression models was constructed by using bulk density, clay percent, sand percent, silt percent, years of cover crop planting, annual temperature, annual rainfall, initial SOC stock, N fertilizer application rate, and cover crop biomass to predict the response ratio (equation 3). However, only studies that provided both cover crop biomass and initial SOC stock were included in the regression modeling. The “stepAIC” function, from the “MASS” package in R studio was used that had combination of both forward and backward regression during model building.

Results and Discussion

Sixty-two articles met the criteria for inclusion in the meta-analysis. These studies resulted in 315 pairs from 70 sites located on 5 different continents (Figure 3). North America (62.8%) had the highest number of sites followed by Asia (11.4%), Africa (10%), South America (8.5%) and Europe (7.14%). Sixteen different countries included in the analysis were United States of America (USA), Brazil, China, India, Argentina, Bangladesh, Benin, Italy, Kenya, Mexico, Pakistan, Poland, South Africa, Spain, Sweden, and Ethiopia (Figure 3). In the USA, most of the studies were in the Cfa, Dfa, and DFb Köppen climate zones. These climate zones are partially aligned with what is referred to as the Corn Belt. Among all studies, 9 were published between 2021 and 2022, 39 were published between 2011 and 2020, 11 were published between 2001 and 2010, and 3 were published between 1990 and 2000. (Figure 4a).

The length of the studies varied with 41, 14, 9, and 6 studies had durations of between 2 and 5, 6 and 10, 11 and 15, and 16 and 20 years, respectively (Figure 4b). The most common soil texture was medium (44.3%) followed by coarse (30 %) (Figure 4c). The studies were conducted in tropical, temperate, and cold climate zones. Of these, most studies were conducted in the temperate (38.5 percent) and cold (45.7 percent) zones (Figure 4d).

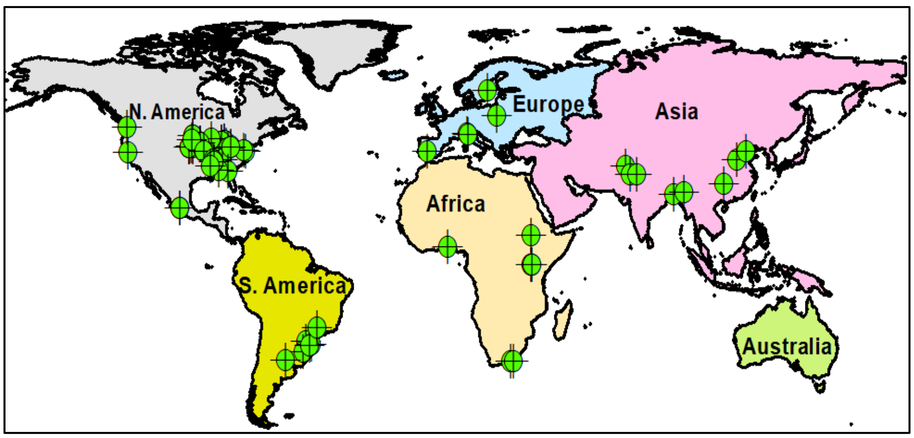
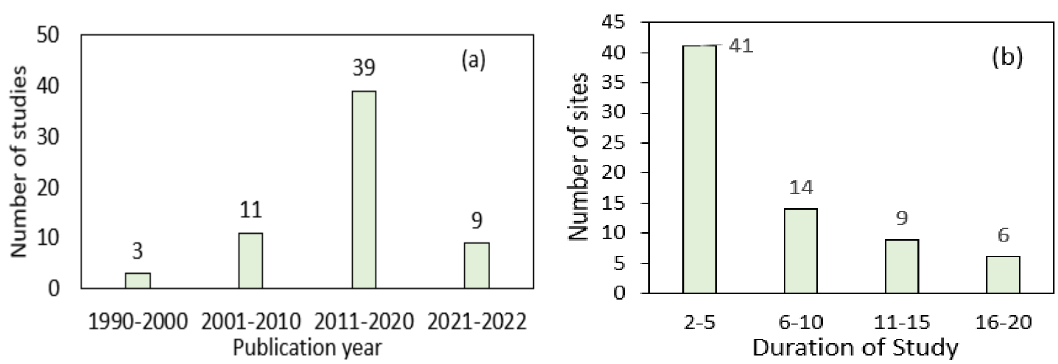


Figure 2. 3. Location of all study sites (green dots) in the world map.



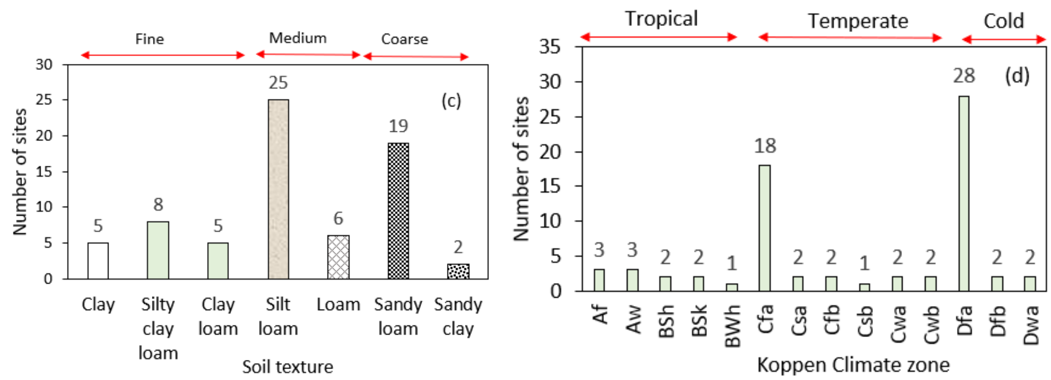


Figure 2. 4. Different categories and their distribution of studies based on a) publication year, b) duration of study, c) soil texture, and d) Köppen climate zone.

Soil organic carbon responses to cover crops

The analysis showed that over all cover crops when compared with the no-cover crop treatment increased SOC by 7.8% (ranged from 5.3 to 10.8%). These findings were consistent with other studies (Abdalla et al., 2019; Jian et al., 2020; McClelland et al., 2021; Poeplau and Don, 2015). The SOC increases were influenced by the amount of above ground cover crop biomass produced, which were affected by climate zone. Most of the study sites in the >7 Mg ha^{-1}category were in the temperate climate region (Ansari et al., 2022; Dube et al., 2012; Tao et al., 2017), whereas most of the study sites in the <3 Mg ha^{-1}category were in the cold climate zone (Bawa et al,2021; Dozier et al., 2017; Moore et al., 2014). In the reported studies, increasing the amount of cover crop biomass produced generally increased SOC storage. For example, in the >7 Mg ha^{-1} biomass category there were 59 pair comparisons, and the SOC increase was 14.7% (ranged from 7.7 to 22.8%). In the 3 to 7 Mg ha^{-1} and < 3 Mg ha^{-1} cover crop biomass categories the average SOC increases were 9.0% (ranged 4.8 to 14.4%) and 4.6% (ranged from 0.6 to 9.0%), respectively (Figure 5). McClelland et al. (2021) also found that carbon storage increased with cover crop biomass production. Though higher biomass category had greater increases, it is important to note that all biomass levels increased SOC. The increase in SOC is important because the data suggest that a portion of CO_2 fixed by the cover crop was stored in the soil. Higher SOC values also suggest that the soils yield potential increased (Clay et al., 2010; Clay et al., 2005; Cotrufo et al., 2013; Joshi et al., 2020).

In the 0 - 15 cm depth, SOC increase by 8.9% (ranged from 6.4 to 12.3%). When averaged over 0- 30 cm zone, SOC increased by 7.0% (ranged from 4.3 to 10.3%) (Figure 5), and when averaged over the 0- 60 cm zone, SOC increased 6.2% (ranged from 2.8 to 10.0%).

The different crop rotations had different amounts of SOC stored (Arif et al., 2021; Balkcom et al., 2013; Sainju et al., 2002; Tautges et al., 2019). In corn followed by corn rotation, cover crops increased SOC 8.6% (ranged from 5.1 to 12.9 %), whereas in the corn followed by soybean rotation, cover crops increased SOC storage 5.1% (ranged from 2.1 to 9.6%) (Figure 5). This apparent crop rotation effect might be due to changes in soil health, differences in the combined amount of cover crop and non-harvested crop biomass produced in the different crop rotations, or the cover crop impact on cash crop yields (Sainju et. al, 2006).

The type of cover crop also influenced SOC. Legume cover crops increased SOC by 9.5% (ranged from 6.7 to 13.4%), whereas a mixed cover crop (multiple species) increased SOC by 8.3% (ranged from 4.5 to 12.9%). A non-legume cover crop only increased SOC by 6.6% (ranged from 4.0 to 9.8%) (Figure 5). These cover crop species differences might be due to variation in total biomass production as well as differences in the C:N ratios. Typically, legume cover crops have lower C: N rations and lower biomass production than non-legume cover crops.

Sites with coarse, medium, and fine soil textures increased SOC by 8.5 (ranged from 3.8 to 14.1%), 6.5 % (ranged from 1.6 to 12.1%) and 8.1% (ranged from 4.6 to 12.4%) respectively (Figure 5). Out of total paired comparisons, 91 had coarse, 108 had fine and 120 had medium textured soils. The increases in SOC with increasing soil coarseness may be attributed soils with coarse soil textures having low initial SOC values (Augustin and Cihacek, 2016). Soils with low initial SOC may have a higher percent increase because the calculation [$\% \, increase = 100 \times {[SOC_{cc,T1} - SOC_{cc,t0}]}/{[SOC_{cc,t0}]}$] is very sensitive to $SOC_{cc,T0}$. This interpretation is consistent with Blanco-Canqui (2022).

SOC storage amount was also influenced by climate zone and tillage. The SOC percent increases in tropical climates were 10.9% (ranged from 4.0 to 19.4%) and SOC increases in cold climates was 6.7% (ranged from 2.9 to 11.1%) (Figure 5). Again, these apparent differences may be related to the initial $SOC_{cc,T0}$ values and that the tropical climates had higher cover crop biomass production (McClelland et al. 2021). SOC storage in no-tillage was 8.5% (ranged from 5.9 to 11.9 %) and SOC storage in tilled systems was 6.6% (ranged from 3.6 to 10.2%) (Figure 5). In U.S. studies, SOC storage in no-tilled soils was 6.9 % (ranged from 3.6 to 10.7 %) and SOC storage in tilled soils was 2.5% (ranged from -0.8 to 5.9%). However, because the confidence interval included 0, the impact of cover crops on SOC storage in U.S tilled soils was not significant. The effect of tillage on SOC storage has been reported by others (Clay et al., 2015). Lower SOC storage in tilled system may be due to the incorporation of the cover crop residue into the soil, and the exposure of protected SOC pools to microbial degradation (Clay et al., 2015; Six et al. 2002).

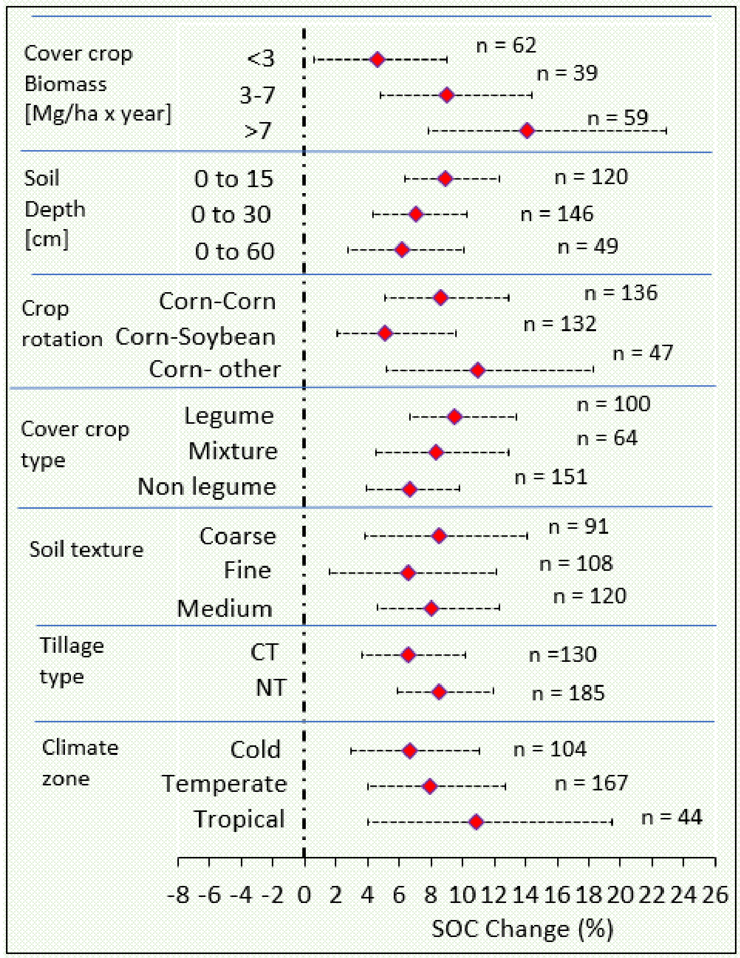


Figure 2. 5. Percent change in SOC due to cover crops compared with no cover crop due to different management and climate factors: cover crop biomass, soil depth, crop rotation, cover crop type, soil texture, tillage, and climate zones. Total number of pairwise comparison are represented by “n”. Error bars are 95% confidence intervals (CIs) and percent SOC change were considered significant only when 95% CIs did not overlap with zero.

Carbon Sequestration potential

The SOC rate of change for the 0 -15 and 0- 30 cm zones were 0.46 (ranged from 0.31 to 0.62), and 0.80 (ranged from 0.56 to 1.05) Mg SOC (ha × year)$^{-1}$, respectively. By subtracting these two depths from each other, carbon storage in the 15 -30 cm zone was determined. This calculation suggests that more carbon was stored in the 0 - 15 cm zone (0.46 Mg SOC (ha × year)$^{-1}$) than the 15 - 30 cm (0.34 Mg SOC (ha × year)$^{-1}$). This analysis is consistent with Clay et al. (2015). A meta-analysis conducted by Poeplau and

Don (2015) reported that for the 0 - 22 cm soil zone, SOC was sequestration at a rate of 0.32 Mg (ha × year)$^{-1}$ in croplands with cover crops. Blanco-Canqui (2022) in an assessment of U.S. studies reported that SOC sequestration rates ranged from 0.2 to 0.9 Mg (ha × year)$^{-1}$ for the 0 - 30 cm soil increment.

Based on the global analysis and the amount of U.S. cover crop cultivated land (6.2 million ha) (Cruthfield, 2016), U.S. corn cropping systems are sequestering approximately 5.0 (ranged from 3.5 to 6.5) million Mg of SOC-C year^{-1} annually. When extended over the globe, the 200 million ha of soil seeded to corn has the potential to sequester approximately 160 (ranged from 112 to 210) million Mg SOC year^{-1} (Wallander et al. 2021; Jian et. al., 2020). However, these estimates are based on the calculated values and have the limitations associated with the published findings. In addition, the actual amount of sequestered C will vary with changes in management, soil, and climatic conditions.

Factors affecting cover crop SOC response

The initial SOC benchmarks, soil clay amount, and annual rainfall were negatively correlated to % carbon increases, whereas cover crop biomass, annual temperature, and N fertilizer rate were positively correlated to [ln(R)] (Table 2). The negative relationship between initial SOC and cover crop induced increases in % SOC storage is predicted by first order kinetics (Clay et al., 2006; Joshi et al., 2020).

Out of 11 different variables that were used in the stepwise multiple linear regression, change in SOC [ln(R)] was best predicted by clay percent, cover crop biomass (CCB), initial SOC at cover crop adoption (SOC_i), annual temperature (t), annual rainfall (r) and N fertilizer application rate. The resulting equation was,

$$\ln(R) = -0.17 - 0.0025\times Clay + 0.0021\times CCB - 0.0013\times SOC_i + 0.03\times t - 0.0001\times r + 0.0003\times N\ rate,\ R^2 = 0.63,\ n = 89,\ p\text{-value} = <0.001 \quad (6)$$

where, clay was in percent, CCB was in Mg (ha x year)$^{-1}$, SOC_i was in Mg SOC-C ha^{-1} , t was in ^{o}C, r was in mm.

USA versus the world

Overall, the U.S. cover crops in corn cropping system increased SOC by 5.4 % (ranged from 1.5 to 9.8%) whereas percent increase outside the US was 11.3% (ranged from 7.4 to 16.4%). The sequestration rate of SOC for the 0 - 15 and 0 -30 cm depths were 0.4 (range from 0.3 to 0.6) and 0.8 Mg SOC-C (ha × year)$^{-1}$ (ranged from 0.4 to 1.2), respectively. Outside of the U.S., the rate of increase was 0.5 Mg SOC-C (ha × year)$^{-1}$ (ranged from 0.3 to 0.8) for the 0-15 cm soil depth and 0.8 Mg SOC-C (ha × year)$^{-1}$ (ranged from 0.5 to 1.3) for the 0-30 cm soil depth. These finding shows that carbon was being sequestered in both the 0 -15 and 15 -30 cm soil depths.

Difference between U.S. and non-U.S. studies may be related to the initial SOC benchmarks, which are often higher in the U.S. than non-U.S. studies (Blanco-Canqui, 2022; Xu et al., 2019). Moreover, most of the U.S. studies are in the temperate climate region whereas out of U.S. studies are in the tropical climate regions.

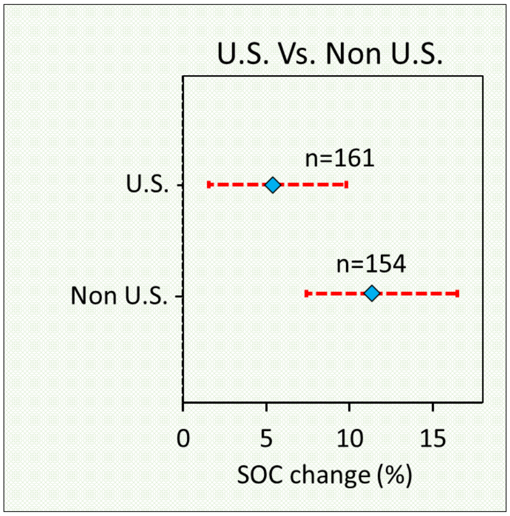


Figure 2. 6. Percent change in SOC due to cover crops compared with no cover crop in USA and rest of world. Total number of pairwise comparison are represented by "n". Error bars are 95% confidence intervals (CIs) and percent SOC change were considered significant only when 95% Cis did not overlap with zero.

Cover crop impact on corn yield

Contrasting results have been recorded globally about the impact of cover crop on the yield of the main crop. For example, cover crop can reduce corn yields (Eckert, 1991; Olson et al., 2014; Ruis et al., 2017), not influence yields (Bich et al., 2014), and increase crop yields (Calegari et al., 2008; Reese et al., 2014; Fronning et al., 2008; Astier et al., 2006). Mixed findings for cover crops impact on corn yields may be attributed to cover crops and main crops competing for water, nutrients, and light (Munawar et al. 1990) and improving nutrient and water use efficiency (Thapa et al., 2018; Thorup-Kristensen et al., 2003). Uncertainties in the yield impacts of cover crops most likely has slowed farmer adoption of cover crops.

In the meta-analysis 158 paired wise comparison from 27 studies were used in this analysis. Analysis showed that the legume cover crops increased corn yields 29% (ranged from 11.6 to 61.5%), that the mixed cover crop increased yields 20% (ranged from 0.7 to 48.2%), and that the non-legume cover crop increased yield 20.7% (ranged from 2.4 to 47.7%) (Figure 7). These results were consistent with Miguez and Bollero(2005) and Marcillo and Miguez (2017). The large corn yield response to the legume cover crops might be due to nitrogen fixation that reduced yield losses due to N stress (Daryanto et al., 2018; Marcillo and Miguez, 2017; Thorup-Kristensen et al., 2003).

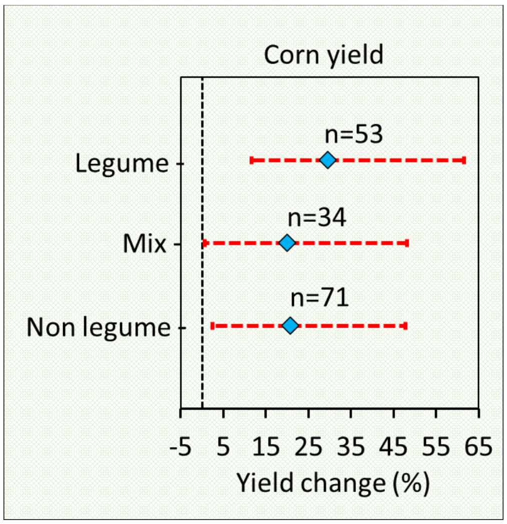


Figure 2. 7. Percent change in corn yield due to different cover crop types compared with no cover crop. Total number of pairwise comparison are represented by “n”. Error bars are 95% confidence intervals (CIs) and percent yield change were considered significant only when 95% CIs did not overlap with zero.

Limitation and future study

Many of the papers failed to report important information used in the meta-analysis. For example, changes in SOC over the entire rooting zone, cover crop biomass produced, cash crop yields, pH, bulk densities, soil texture and nutrient concentrations were often not reported. Not reporting important information, such as yields of the cash crop, or the amount of cover crop biomass reduces the ability to evaluate important interactions. Others have reported similar gaps in what is reported (Abdalla et al. 2019; Jian et al. 2020; Poeplau and Don 2015). To improve global predictive models, these data base gaps need to be minimized.

Conclusions

In this analysis, data from 62 publications were used to determine the effects of cover crops on SOC within a corn cropping system. A data base was created by extracting information provided by the individual studies along with global soils and climate information. Based on this information, the effect of cover crops on SOC response ratio and relationship among the SOC response ratio and the soil chemical and physical properties were determined. Globally, using a cover crop in a corn production system increased SOC 7.8% (ranged from 5.39 to 10.82%). SOC storage was positively correlated with cover crop biomass and temperature and negatively correlated with SOC_i. The negative correlation between initial SOC and carbon storage is consistent with first order kinetics (Joshi et al., 2020). In this analysis, percent carbon increases were highest in systems that used legume cover crops and no-tillage. Current corn fields with cover crops that have a SOC sequestration rate of 0.8 Mg (ha × year)$^{-1}$ are potentially sequestering 5.0 million Mg of SOC-C year^{-1} in the U.S. and 160 million Mg SOC year^{-1} globally. If all U.S. corn fields used cover crops, 29.1 million Mg SOC year^{-1} could be sequestered annually in the U.S., which would result in a CO_{2e} value of 107 million metric tons.

These findings imply that cover crop induced increases in SOC can improve soil health and the soils yield potential. Higher yield potential may be responsible for the cover crop induced yield increases. Findings from this study can be used to identify areas that may have the greatest potential to sequester carbon. However, these models may be limited in scope because many studies do not report important information. After conducting worldwide meta-analysis, we found that growing cover crops on cropland rather than leaving it in a fallow phase improves SOC stock and serves as an effective approach to mitigate for anthropogenic greenhouse gas emissions.

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Table 2. 1 Summary of the studies included in the meta-analysis.

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
1	Argentina	2006-2014	17.6	1042	silt loam	winter wheat	NT	CS	Romaniuk et al. 2018
2	Bangladesh	2010-2011	25.65	1493.2	clay loam	Sesbania, Thornless lazzobati & Mungbean	CT	RC	Salahin et al. 2013
3	Benin	1988-1999	27	1200	sandy loam	Mucuna pruriens	NT	CC	Barthes et al. 2004
4	Brazil	1991-1998	19.7	1769	sandy loam	Mucuna	NT	CC	Bayer et al. 2009
5	Brazil	2013-2017	11.6	1500	Clay	fodder radish, vetch, black oat, white oat, canola, rye grass & red clover	CT	CC	Locatelli et al. 2020
6	Brazil	2001-2012	16	1480	clay	rye, oats, ryegrass, wheatgrass & sudan grass	NT	CC	Grohskopf et al. 2016
7	Brazil	2000-2016	22.2	1425	Sandy clay	velvet bean, jack bean & millet	NT	CC	Bettiol et al. 2022
8	Brazil	1986-2005	19.32	1350	high clay	vetch, winter wheat, radish, oat & lupin	NT	CS	Calegari et al. 2008
9	China	2017-2019	15.9	531.5	sandy loam	violet cress	CT	WC	Zhang et al. 2021
10	China	2012-2014	15.3	1308.1	loam	Vicia villosa, common vetch, milk vetch & radish	CT	CC	Tao et al. 2017

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
11	China	1980-2012	11.6	607	clay loam	Green manure	CT	RC	Yang et al. 2015
12	Ethiopia	2007-2008	21.6	1422.45	Clay	Cowpea, black dessie, awash melka & soybean	NT	CC	Hirpa et al. 2013
13	India	2014-2015	24.71	700	sandy loam	pearl millet, fodder maize, sorghum	CT	CC	Singh et al. 2020
14	India	2012-2017	21.5	1545.5	sandy clay loam	green gram, cowpea & sesbania	CT	CG	Ansari et al. 2022
15	Italy	2009-2013	14.1	885	sandy loam	rye & hairy vetch	NT	CS	Maris et al. 2021
16	Italy	2016-2019	13.1	830	clay loam	rye, phacelia, white mustard, Italian rye, crimson clover, Persian clover & hairy vetch	NT	CS	Fiorini et al. 2022
17	Kenya	2008-2009	21	1978	clay loam	Mucuna pruriens	CT	WC	Ngome et al. 2011
18	Mexico	1995-2000	14.5	1000	sandy loam	vetch & ayocote bean	NT	CC	Roldan et al. 2003

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
19	Mexico	1997-1998	14	1100	sandy loam	vetch & oat	CT	CC	Astier et al. 2006
20	Pakistan	2015-2017	20.13	360	silt clay loam	Sesbania	CT	WC	Arif et al. 2021
21	Pakistan	2017-2018	23.84	375	sandy loam	Egyptian clover	CT	CC	Shabir et al. 2020
22	Poland	1980-2013	7.8	560	sandy loam	Mustard	CT	CWBClov	Martyniuk, et al., 2019
23	South Africa	2007-2011	18.1	848.36	sandy loam	oat & vetch	NT	CC	Dube et al. 2012
24	South Africa	2009-2011	18.1	298.5	sandy loam	oat & vetch	CT	CC	Mukumbareza et al. 2016
25	Spain	2002-2004	19.16	480	clay loam	Oat	NT	CC	Muñoz et al. 2007
26	Sweden	1999-2009	5.4	570	clay loam	rye, oats, ryegrass, wheatgrass & sudan grass	CT	CC	Menichetti et al.,2015
27	USA	1982-1985	9.5	965	silt loam	Rye	NT	CC	Eckert et al. 1991
28	USA	1984-1995	14.91	1324.6	silt loam	vetch & winter wheat	NT	CC	Mullen et al. 1998
29	USA	1994-1999	17.13	927.4	sandy loam	vetch	NT	TC	Sainju et al. 2002
30	USA	2001-2008	14.98	1301.7	silt loam	vetch & rye	NT	CS	Olson et al. 2010
31	USA	1994-2007	12.09	1695	silt loam	Rye	NT	CC	Steele et al. 2012

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
32	USA	2003-2009	18.83	1542.8	sandy loam	rye & wheat	NT	CCot	Balkcom et al. 2013
33	USA	2010-2013	10.2	714.1	silt loam	rye	NT	CC	Blanco-Canqui et al. 2014
34	USA	2001-2012	14.88	1337.31	silt loam	Hairy vetch & rye	NT	CS	Olson et al. 2014
35	USA	2005-2009	6.38	596.39	silt clay loam	winter lentils & slender wheat grass	NT	CS	Wegner et al. 2015
36	USA	2011-2015	13	977	sandy loam	rye	CT	CS	Beehler et al. 2017
37	USA	2013-2016	10	818	silty clay loam	rye	NT	CC	Ruis et al. 2017
38	USA	2008-2015	9.1	849	loam	rye	NT	CC	Ibrahim et al. 2018
39	USA	2008-2012	8.7	821	silty clay loam	rye	NT	CC	Obrycki et al. 2018
40	USA	2012-2015	10.17	716	silt loam	mix	NT	CS	Sharma et al. 2018
41	USA	2006-2013	10.1	1005	sandy loam	rye	NT	CS	Snapp and Surapur 2018
42	USA	2005-2012	6.61	669.2	silt clay loam	winter lentil & wheatgrass	NT	CS	Wegner et al. 2018
43	USA	2005-2015	6.44	654.8	silt loam	rye & vetch	NT	CS	Chalise et al. 2019
44	USA	2015-2016	12.05	709.7	silt loam	winter rye	NT	CC	Sindelar et al. 2016

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
45	USA	1993-2012	17.57	650	silt loam	Pie, hairy vetch, faba bean & cereal oat	CT	CT	Tautges et al. 2019
46	USA	2008-2017	9.1	850	loam	winter rye	NT	CC	Ye. et al. 2020
47	USA	2013-2015	9.97	1110	silt clay loam	Spring oat, red clover, cereal rye, hairy vetch, rye grass, rape	NT	CS	Dozier et al. 2017
48	USA	2012-2013	11.3	1015	silt loam	forage radish, buckwheat, hairy vetch & cereal rye	CT	CS	Welch et al. 2016
49	USA	1987-1992	11.28	980.4	silt loam	Rye, australian winter pea, rye grass, hairy vetch & canola	CT	CC	Kuo et al. 1997
50	USA	2002-2003	10.23	1180	silt loam	rye & hairy vetch	CT	CC	Villamil et al. 2006
51	USA	1997-2006	10.86	810	silt loam	perennial rye, annual rye, red fescue and blue grass	CT	CSunS	Shrestha et al. 2013
52	USA	2014-2017	6.8	869	silt loam	rye	CT	CC	Cates et al. 2019
53	USA	2016-2018	11.7	793.43	loam	Winter barley, winter cereal rye, winter triticale & winter oat	NT	CS	Rankoth et al. 2019
54	USA	2001-2014	14.8	1070	silt loam	rye, oats, ryegrass, wheatgrass, sudan grass	NT	CSCot	Ashworth et al. 2018

SN	Location	Duration	Annual Temperature (C)	Annual Rainfall (mm)	Soil texture	Cover crop type	Tillage type	Crop rotation	References
55	USA	1969-2007	11	1113.536	silt loam	vetch, peas, beans, alfalfa & clover	NT	CSW	Lopez-Bellido et al. 2010
56	USA	2009-2011	9.23	1019.1	loam	rye	NT	CS	Moore et al. 2014
57	USA	2002-2018	14.8	1070	silt loam	hairy vetch & winter wheat	NT	CSCot	Bansal et al. 2021
58	USA	2017-2020	8.23	724	silty clay loam	rye	NT	CS	Bawa et al. 2021
59	USA	2016-2019	13.8	1000.2	silt loam	rye & radish	NT	CC	Young et al. 2020
60	USA	2015-2018	16.8	1490	silt loam	rye, radish & clover	NT	CS	Jacobs et al. 2022
61	USA	2001-2004	7.8	756.5	sandy loam	rye	NT	CS	Fronning et al. 2008
62	USA	2007-2012	9.4	1100	silt loam	mix	NT	CS	de Paul Obade et al. 2014

Chapter 3

Quantification and Machine Learning Based N_2O-N and CO_2-C Emissions Predictions from a Decomposing Rye Cover Crop

Abstract

Cover crops improve soil health and reduce the risk of soil erosion. However, their impact on the carbon dioxide equivalence (CO_{2e}) is unknown. Therefore, objective of this two-year study was to quantify the effect of cover crop-induced differences in soil moisture, temperature, organic C, and microorganisms on CO_{2e} and to develop machine learning algorithms that predict daily N_2O-N and CO_2-C emissions. The prediction models tested were multiple linear regression (MLR), partial least square regression (PLSR), support vector machine (SVM), random forest (RF), and artificial neural network (ANN). Models' performance was assessed using R^2, RMSE and MAE. Rye (*secale cereale*) was dormant seeded in mid-October and in the following spring it was terminated at corn's (*Zea mays*) V4 growth stage. Soil temperature, moisture, and N_2O-N and CO_2-C emissions were measured near continuously from soil thaw to harvest in 2019 and 2020. Prior to termination, the cover crop decreased N_2O-N emissions by 34% ($p=0.05$) and over the entire season, N_2O-N emissions from cover crop and no cover crop treatments were similar ($p=0.71$). Based on N_2O-N and CO_2-C emissions over the entire season and the estimated fixed cover crop carbon remaining in the soil, the partial CO_{2e} were -1,061 and 496 kg CO_{2e} ha^{-1} in the cover crop and no cover crop treatments, respectively. The RF algorithm explained more of the daily N_2O-N (73%) and CO_2-C (85%) emissions variability during validation than the other models. Across models, the

most important variables were temperature and the amount of cover crop-C added to the soil.

Introduction

Techniques to reduce agricultural greenhouse gas (GHG) emissions are needed to lower unknown future climate risks (Joshi et al., 2021; Shrestha et.al., 2019; Skinner et al., 2019). Of the numerous techniques proposed, planting a cover crop is a technique that can be rapidly adopted by many farmers (McClelland et al., 2021). Despite many studies, there is no conclusive evidence that cover crops reduce the CO_{2e} (Basche et al., 2014; Behnke and Villamil, 2019; Thies et al., 2020; Reicks et al., 2021).

A growing cover crop can reduce soil moisture, inorganic N, and temperatures which in turn can reduce N_2O emissions (Cayuela et al., 2009; Thapa et al., 2018; Reicks et al., 2021). However, after cover crop termination the effect of the decomposing cover crops on GHG emissions is unclear (Antosh et al., 2020; Basche et al., 2016; Basche et al., 2014; Çerçioğlu et al., 2019). During cover crop decomposition, the release of inorganic N and organic substrates may increase and N_2O-N and CO_{2-}-C emissions. To quantify the effect of cover crops on the carbon footprint, the CO_{2e} for the entire season must be determined. The CO_{2e} equivalence combines all GHG into a single value. However, due to the high cost of intensive trace gas measurements few studies measure emissions for the entire life cycle of both the cover and cash crops.

Aside from the difficulty of measuring N_2O-N and CO_2-C emissions, accurate and precise models are needed to provide guidance on how climate and management changes impact sustainability and GHG emissions. However, many process-based models are difficult to use, may not provide the desired accuracy (Sozanska et al., 2002; Roelandt et al., 2005; Zhang et al., 2016; Necpálová et al., 2015; Jiang et al., 2018), may require long-term field histories, and may not accurately predict management responses in real systems (Hamrani et al., 2020; Del Grosso et al., 2000, 2001; Jiang et al., 2018). In addition, following calibration process-based models often have a mixed ability to predict N_2O emissions. For example, McClelland et al. (2021) used the DAYCENT model to predict the effect of cover crops on N_2O emissions. This work showed that the predicted and observed N_2O emissions were not correlated. In Colorado, Del Grosso et al. (2008) reported that DAYCENT overestimated N_2O emissions, whereas in Iowa, Jarecki et al. (2006) reported that DAYCENT over predicted emissions when the actual emissions were low and underestimated emissions when emissions were high. The mixed results of the model's ability to predict N_2O-N emissions may be attributed to many factors including field experiments that do not accurately measure N_2O-N emissions, process-based models that were not accurately parametrized, and/or mathematics that do not accurately describe the complexity of the system.

An alternative approach is to use the machine learning (ML) algorithms to predict GHG emissions. These models may be easier to use because they can be based on easy to measure values, may require fewer input variables than process-based models, and can be modified to account for different spatial and temporal resolutions. Therefore, the objectives were to quantify the effect of cover crop-induced differences in soil moisture, temperature, organic C, and microorganisms on CO_{2e} and to develop machine learning algorithms that can predict daily N_2O-N and CO_2-C emission.

Materials and Methods

Study Site, Experimental design, and treatments

The two-year study was conducted at the South Dakota State University Aurora Research Farm located at 44°18′20.57′′N and 96°40′14.04′′W in 2019 and 2020. The site was in the Dfb (warm humid continental climate) Köppen climatic subtype. The soil at the experimental site was a Brandt silty clay loam (fine-silty, mixed, superactive cold Calcic Hapludoll). The soil organic carbon content was 36 Mg ha^{-1} (1.8% SOC), and the surface 15 cm contained 28 g clay kg^{-1} and 650 g silt kg^{-1} (Reicks et. al., 2021). The production practices were a corn- corn rotation, no tillage, and N fertilizer was not applied.

The experimental design was completely randomized with two treatments: cover crop and no-cover crop. Each treatment was replicated 4 times. The dimensions for each experimental unit was 9.1 × 3.1 m. Winter cereal rye (*Secale cereale*) was drilled in two rows at a rate of 56 kg ha^{-1} at a depth of 2.5 cm in October in the fall of 2018 and 2019. The two cover crop rows were separated by 17.5 cm, and they were positioned in the center between 2 corn rows. The cover crop occupied about 25% of the area between the corn rows.

In the following spring, a 97-day relative maturity corn (*Zea mays*) cultivar was planted at the rate of 79,000 seeds ha^{-1} at a depth of 5 cm close to the rows of the previous corn crop. The row spacing was 76 cm. At V4 growth stage of corn and boot stage of rye, rye was terminated using glyphosate [N-(phosphonomethyl) glycine); Roundup Power Max] at the rate of 2.34-liter ha^{-1}. A non-ionic surfactant was added at 0.25% of the spray solution. Ammonium sulfate was also added to the spray solution at

10.2 g L^{-1}. Corn was harvested on 26 September 2019 and 8 October 2020. More details about field activities are provided in Table 1.1.

Table 3. 1 Summary of activities and dates of operations performed during the two-year experiment.

Field activities and operations	2019	2020
Rye cover crop dormant seeded	16-Oct-18	23-Oct-19
GHG measured in growing cover crop	April 26 to June 24	April 8 to June 24
Corn planted	16-May	14-May
Rye cover crop termination at boot stage (corn V4). Soil samples and rye tissue samples collected.	24-Jun	24-Jun
GHG measurements started at rye cover crop termination.	24-Jun	24-Jun
Corn harvest	26-Sep	8-Oct
Termination of GHG measurements. Soil samples collected.	21-Oct	21-Oct

GHG emission measurements

Nitrous oxide-N and CO_2-C emissions were measured from cover crop termination to harvest using techniques described in Reicks et al. (2021). Glyphosate was used to kill the cover crops, but because the rye at termination was taller (approximately 45 cm) than the rings (6cm above soil surface), the plants were bent and twisted such that the cover crop fit inside the rings. At the corn V4 growth stage, PVC pipe rings 12-cm tall having a diameter of 20-cm and a surface area of 317 cm^2 were randomly placed in the production plots with and without cover crops. In plots with cover crops, the PVC rings were centered on the cover crop rows, whereas in plots without cover crops, the rings were centered between the corn rows. For GHG measurement, eight PVC rings (4 per treatment) were pushed 6 cm into the soil with 6 cm remaining above the soil surface. Directly before termination, similar rings were placed adjacent to the GHG microplots in the cover crop treatment. The cover crop within the ring was clipped near the soil surface, dried, weighed and analyzed for C and N in the laboratory.

To collect GHG from the microplots, the PVC rings were covered with LI-COR long-term opaque chambers (8100-104 LI-COR) six times daily for 15 minutes at four-hour intervals (between 0000 and 0230 h, 0400 and 0630 h, 0800 and 1030 h, 1200 and 1430 h, 1600 and 1830 h, and 2000 and 2230 h) (Reicks et al. 2021). Using a Picarro Cavity Ringdown Spectrometer (model G2508, Picarro Inc, Santa Clara, CA), gases extracted from the chambers were analyzed for N_2O-N and CO_2–C concentrations. Emissions were calculated using the LI-COR SoilFluxPro 4.01 software (v. 4.01; LI-COR). Standard N_2O, and CO_2 gases were used at the beginning and end of the experiment to ensure Picarro gas analyzer accuracy. Soil moisture and temperatures for the surface 0 to 5 cm were measured using LI-COR LI-8150-205 Soil Moisture Probes and LI-COR LI-8150-203 Soil Temperature Probes (LI-COR), respectively.

Soil sampling

Soil samples were collected from the 0 to 15 and 15 to 30 cm depth at cover crop termination in area adjacent to the PVC rings to avoid soil disturbance within the ring on June 24 (cover crop termination) and from inside the ring at the termination of the experiment on October 21 (each year) following corn harvest. Soil samples from the 0 to 15 cm depth was analyzed for bulk density, gravimetric soil moisture, inorganic N, soil organic carbon and the soil microbial community (Table 1.1). Samples from the 15 to 30 cm depth were analyzed for bulk density, gravimetric soil water, inorganic N, and soil organic carbon. Gravimetric soil moisture content and bulk densities were determined by drying the soil at 105 ^{o}C for 24 hours. Air dried subsamples were ground and analyzed for total C and N, NH_4^{+}–N and NO_3^{-}–N (Clay et al., 2015).

Soil microbial biomass and composition

Soil samples were collected from 0 to 15 cm soil depth at the same timings as above for microbial biomass and composition following procedures outlined in Veum et al. (2019). Microbial community composition was determined using PLFA (Phospholipid Fatty Acid) protocols described by Buyer and Sasser (2012), Thies et al. (2019), and Fiedler et al. (2021). In this analysis, 19:0 phosphatidylcholine was used as an internal standard for PLFA and a 19:0 trinonadecanoin glyceride was used as an internal standard for NLFA (neutral lipid fatty acids).

A Shimadzu GC-2010 Plus gas chromatograph (Shimadzu Corporation, Japan) with a flame ionization detector was used to analyze the extracts. The PLFAD2 method was used to calibrate the gas chromatograph using a standard provided by MIDI Sherlock (No. 1208, MIDI, Inc., Newark, DE). Using the MICSOILV2 approach from the MIDI Sherlock Software system (MIDI, Inc., Newark, DE) fatty acids were assigned to distinct functional groups associated with each community type to determine the number and types of microorganisms within the microbial population (Veum et al., 2019). Terminally branched chain fatty acids were used to identify gram-positive bacteria, while monounsaturated and hydroxy substituted fatty acids were used to identify gram-negative bacteria. Methyl branched chain fatty acids were used to identify actinomycetes (Zhang et al., 2016). Total microbial biomass was the summation of all fatty acids (Quideau et al., 2016).

Statistical Analysis

Carbon dioxide equivalence (CO_{2e})

The experiment used a completely randomized design where each treatment was replicated 4 times per treatment. Total N_2O-N and CO_2-C emissions were determined by integrating the emissions over the study period. The experiment was repeated in 2019 and 2020. The analysis of variance was conducted to compare the total N_2O-N and CO_2-C emissions, inorganic nitrogen, total carbon, and microbial population from each treatment using "agricolae" package in Rstudio (R core Team 2019). Tukey HSD test was conducted after ANOVA analysis to determine significant differences between treatment means at p-value 0.05.

Based on the cover crop occupying 25% of the area between the corn rows the N_2O-N and CO_2-C emission data were area corrected. For this correction, the emissions from the cover crop were multiplied by 0.25 which was added to product of 0.75 times the emissions from the no-cover crop. The CO_{2e} was determined by converting N_2O-N kg ha^{-1} values to N_2O kg ha^{-1} and CO_2-C kg ha^{-1} to CO_2 kg ha^{-1}. The N_2O was then converted to CO_{2e} determined by multiplying N_2O by 298. The partial CO_{2e} value was the summation of $CO_{2e\ N2O}$ and CO_2 which was then subtracted from the amount of CO_2 that was fixed by the cover crop during the growth phase. This analysis did not consider the effect of the cover crop on methane emissions or any factors other than those directly involved in the production of N_2O-N and CO_2-C during the cover and cash crop growing seasons.

Machine learning models

"Hmisc" package and "rcorr" function in Rstudio was used to determine the Pearson's correlation (r) between all the variables. Following correlation analysis of all the variables, CO_2-C and N_2O-N emissions were predicted using five models. Those five models tested were multiple linear regression (MLR), partial least square regression (PLSR), support vector machine (SVM), random forest (RF) and artificial neural network (ANN). MLR model was considered the traditional linear regression model whereas rest of the models were machine learning models. The PLSR method is well-known for its ease of use when dealing with highly correlated variables. It was selected because it generalizes and combines features from principal component analysis and multiple linear regression (Abdi, 2003). The SVM algorithm creates a line or a hyperplane which separates the data into different classes. The line or hyperplanes are considered as the decision boundary, and they are utilized to predict continuous outputs. It was selected due to its ability to solve non-linear regression prediction problem (Ahmad et al. 2014). The non-linear "svmRadial" algorithm from the R “caret” package was utilized to implement SVM in our analysis. The RF is a machine learning (ML) algorithm for classification and regression which is based on the recursive partitioning principle, and specific information about the relationships between the response and predictor variables is not required (Breiman, 2001; Hamrani et al., 2020; Sharma et al., 2022). It creates a forest with several decision trees. With the RF approach, the accuracy and robustness of model is directly correlated with the number of trees in the forest (Breiman, 2001). The ANN adapts to the computing environment by adjusting neuron weights and thresholds repeatedly. When the network's output error approaches the expected value, the network training is complete. This model is gaining in popularity because of its ability to develop predictive relationships even when there is not a coherent theoretical framework (Maind and Wankar, 2014). The model predicted daily emissions, that were calculated by integrating the hourly measurements (every 4 hours = 6 samples/ day). The whole dataset was randomly divided into training (75%) and validation (25%) datasets. On the training data set, k-fold cross-validation (CV) was carried out for resampling procedures using "caret" package. The CV technique splits the data into different folds, estimates the error rate based on machine learnings algorithms, and then generates the final model with the lowest error rate (Yank et al., 2011). In this work, 10 folds with three replications of the repeated k-fold CV were used. The model performance was assessed by comparing the coefficients of determination (R^2), root mean square errors (RMSE), and mean of absolute value of error (MAE) that were determined with the equations,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_p)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad \text{[Eq 1]}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_p)^2} \qquad \text{[Eq 2]}$$

$$\text{MAE} = \frac{|(y_i - y_p)|}{n} \qquad \text{[Eq 3]}$$

where y_i and y_p were measured and predicted values (N_2O-N or CO_2-C) respectively, and $\overline{y_i}$ was the mean of all measured values and n was the number of samples. All the models were built using "caret" package (Version 6.0-88) in Rstudio. In the model, N_2O-N and CO_2-C were used as dependent variables whereas soil temperature, air temperature, soil moisture, amount of cover crop-C remaining, and rainfall were used as predictor variables. The best performing models has high R^2 (closer to 1) and low RMSE and MAE values.

The total daily cover crop-C was calculated using equations 4 and 5 as shown below,

$$CO_2\text{-}C_{CC\ emitted} = [CO_2\text{-}C_{CC+soil\ emitted}] - [CO_2\text{-}C_{soil\ emitted}] \qquad [Eq\ 4]$$

where CO_2-$C_{CC\ emitted}$ was the daily amount of CO_2-C that was mineralized from the cover crop over a 24-hour period, CO_2-$C_{CC\ +\ soil\ emitted}$ was the total amount of CO_2-C that was emitted over a 24-hour period in cover crop treatment, and CO_2-$C_{Soil\ emitted}$ was the total amount of CO_2-C that was emitted over a 24-hour period in the no-cover crop treatment. The amount of cover crop-C remaining in the soil was calculated with the equation,

$$\text{Cover crop-}C_{remaining} = [\text{Cover crop-}C_{initial}] - [CO_2\text{-}C_{CC\ emitted}] \qquad [Eq\ 5]$$

where, Cover crop-$C_{remaining}$ was the amount of cover crop-C remaining in the chambers, [Cover crop-$C_{initial}$] was the amount of cover crop-C in the soil when the cover crops were termination, and CO_2-$C_{CC\ emitted}$ was defined in equation 4.

The importance of the variables was determined following validation. Variable importance was determined using the "varImp" function from the “caret” package. The function used scaled important score between 0 to 100. The higher the score the more important.

Results and Discussion

Weather and climatic conditions

At the study area, the 30-year (1989 to 2019) average annual rainfall was 640 mm, the average growing season rainfall (May to September) was 452 mm, the average growing degree days (10 ^{o}C base and 30 ^{o}C maximum temperature) from April to October was 1256 GDD’s, the average annual temperature was 6.3 ^{o}C, and the growing season average temperature was 17.9 ^{o}C (NOAA, 2022). At the study site, the average annual and growing season temperature in 2019 were 5.37 and 17.9 ^{o}C, whereas in 2020 it was 7.15 and 18.9 ^{o}C respectively (Figure 3.1). Total annual rainfall in 2019 was 825 mm of which 607 mm occurred during the growing season. In 2020, total rainfall was 441 mm of which 324 mm occurred during the growing season. In 2019 and 2020 the numbers of accumulated growing degree days based on corn were 1266 and 1436, respectively. Additionally, from 1 October 2018 to 31 March 2019 and from 1 October 2019 to 31 March 2020 the average snow depth was 8.7 cm and 12 cm, respectively. The temperature of the snow-covered soil at 0 to 5 cm depth, ranged from -5.12 to 13.17 ^{o}C in 2019 and from -0.93 to 13.99 ^{o}C in 2020. Between cover crop termination and harvest, the soil moisture content of the cover crop treatment in the 0 to 5-cm soil depth was greater (0.32 cm^3 cm^{-3}) than the no-cover crop treatment (0.26 cm^3 cm^{-3}) (Table 3.2). On average across years, the average soil temperature for the surface 0 to 5cm was 3.1 ^{o}C cooler in the cover crop (14.2 ^{O}C) than the no-cover crop (17.3 ^{o}C) treatment.

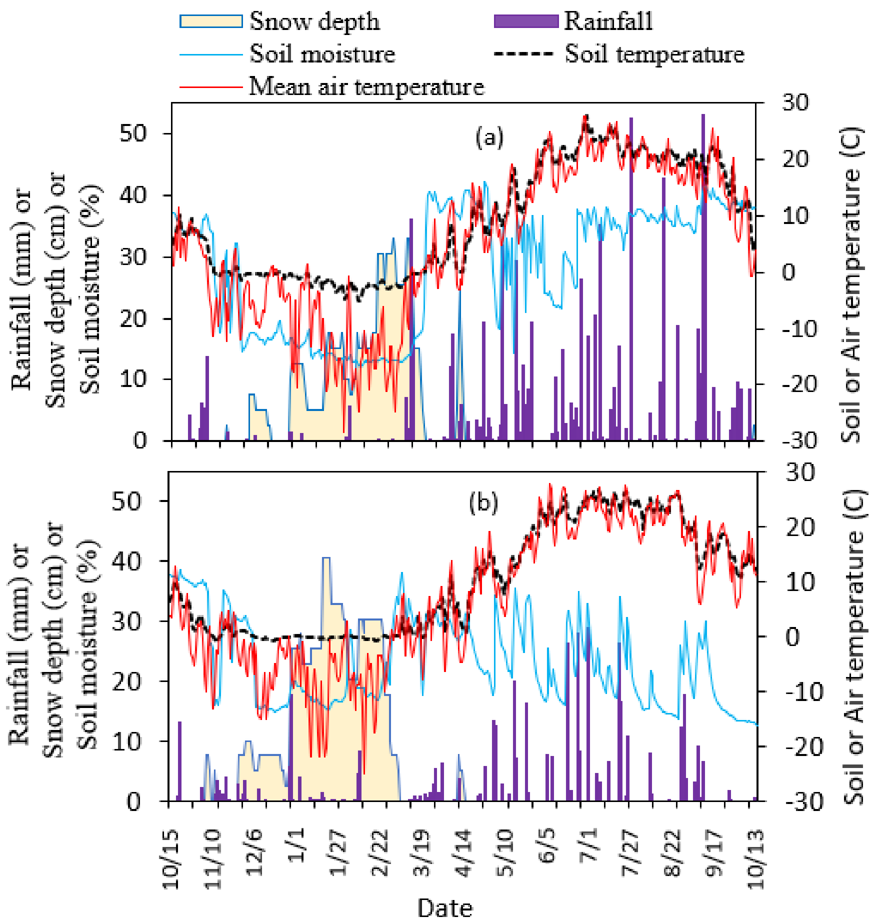


Figure 3. 1. Daily distribution of snow depth, rainfall, air temperature, soil moisture, and soil temperature during first (Oct 2018- Oct 2019) (a) and second (Oct 2019- Oct 2020) (b) year of experiment. Data source: South Dakota Mesonet (2022).

Cover crop biomass and corn grain yield

The amount of dried above-ground rye biomass contained within the microplot was 4156±576 and 3166±353 kg biomass ha^{-1} in 2019 and 2020, respectively. Based on previously reported value of 0.497 g root (g shoot)$^{-1}$ for the root to shoot ratio (Sawyer et al., 2017), the amount of rye roots was calculated. Rye roots were then multiplied by 2 to estimate the root exudates (Kuzyakov and Domanski, 2000; Kuzyakov and Larionova, 2006). Finally, to determine total rye biomass the shoot + root + root exudates were summed which was then multiplied by the amount of carbon in the above ground biomass samples [0.42 g carbon (g biomass)$^{-1}$]. The amount of cover crop-C added to each chamber was 4,349 and 3,312 kg C ha^{-1} in 2019 and 2020, respectively. The measured C to N ratio of the above ground cover crop biomass was 31:1 and 25:1 in 2019 and 2020, respectively. Based on these values, the amount of N contained in the above ground cover crop biomass was 56 and 43 kg N ha^{-1} in 2019 and 2020, respectively. This calculation does not consider N contained in root biomass.

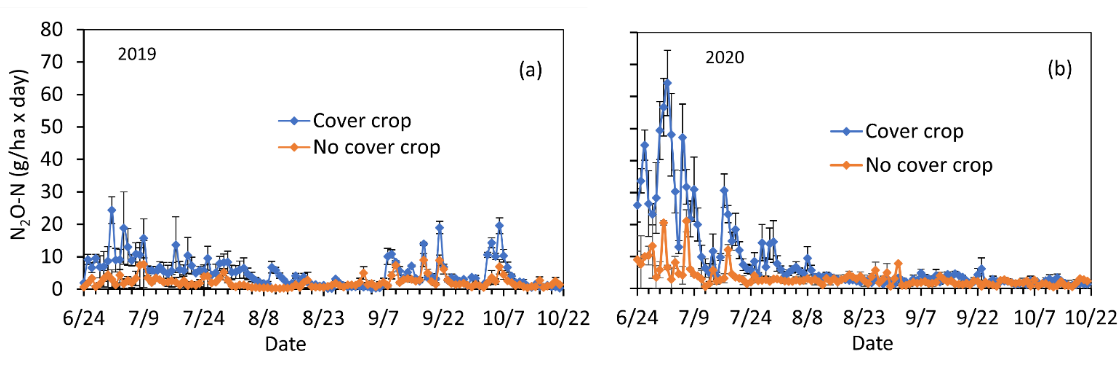
The above cover crop C and N values represent the additions to area between the corn rows that were seeded with cover crops. The area seeded with cover crops represented about 25% of the area between corn rows. Based on this percentage, the amount of cover crop biomass in the production plot was 1120 and 702 kg biomass ha^{-1} in 2019 and 2020, respectively.

The effects of the cover crop on corn growth and yield have been reported by Miller et al. (2021). Across years, corn grain yields at 15.5% moisture ranged from 7.7 to 12.8 Mg ha^{-1}. The no cover crop treatment had 40% greater yield than treatment with cover crop that was terminated at corn's V4 growth stage.

N_2O and CO_2 emissions

N_2O-N and CO_2-C emissions in 2019 and 2020 were separated into two periods when the cover crops were growing and when they were decomposing. Reicks et al. (2021) reported on emissions between soil thaw and cover crop termination at V4. To summarize, this growth period N_2O-N emissions were 90 and 192 g ha^{-1} in the cover crop and no-cover crop treatments in 2019, respectively. In 2020, similar results were observed, and N_2O-N emissions were 168 and 209 g N_2O-N ha^{-1} in the cover crop and no-cover treatments, respectively. Lower N_2O-N emissions in the cover crop compared with the no-cover crop treatment was attributed to the cover crop reducing soil moisture and inorganic N (Reicks et al. 2021). Due to higher soil temperatures, N_2O-N was slightly higher in 2020 than 2019. Based on these values, the cover crop-induced decrease (cover crop - no-cover crop) in N_2O-N emissions was 0.11 in 2019 and 0.04 kg ha^{-1} in 2020. These decreases were equivalent to 0.42 and 0.78% of the N contained in the above ground cover crop biomass. Higher emissions in 2020 than 2019, were attributed to higher temperatures and nitrous oxide being produced during nitrification and denitrification.

Greater N_2O-N emissions were observed during cover crop decomposition than the growth phase. In 2019, N_2O-N emissions in the cover crop and no-cover crop treatments were 537 and 301 g N_2O-N ha^{-1} and in 2020 N_2O-N emissions in the cover crop and no-cover crop treatments were 953 and 537 g N_2O ha^{-1}, respectively (Figure 3.2, Table 3.2). Differences in N_2O-N emissions during the growth and decomposition cover crop phases were attributed to the decomposing cover crop biomass releasing NH_4^+ into the soil. The NH_4^+ was subsequently nitrified of which 0.03 to 1% of the N can be emitted as N_2O-N (Farquharson, 2016).



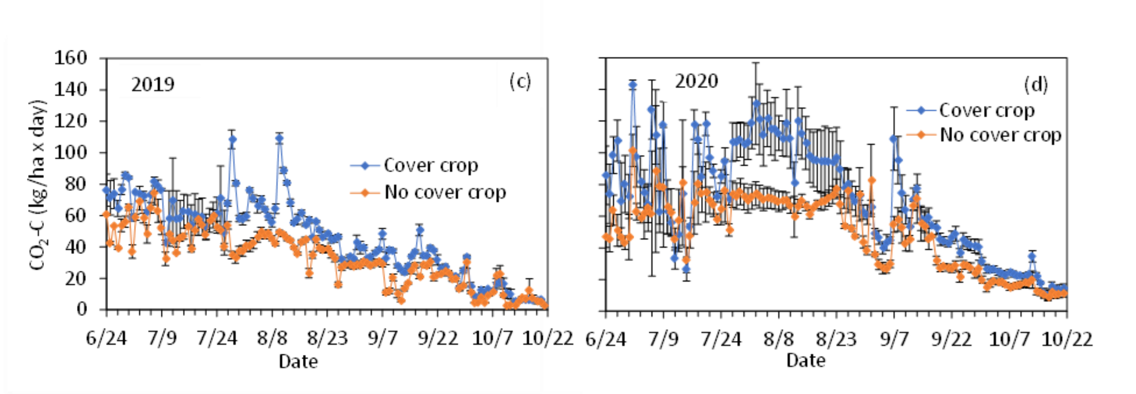


Figure 3. 2. The impact of the rye cover crop on daily average N_2O-N (a and b) and CO_2-C (c and d) emissions in 2019 and 2020. Error bars represent standard error (SE) (n=4).

The amounts of CO_2-C that was emitted in 2019 prior to corn's V4 growth stage were 1379 and 882 kg CO_2-C ha^{-1} in the cover crop and no-cover crop treatment, respectively (Reicks et al. 2021). During decomposition, CO_2-C emissions within the chambers were 5093 and 3935 kg CO_2-C ha^{-1} in the cover crop and no-cover crop treatment, respectively. The cover-crop induced increase in CO_2-C emissions represented 27% of the estimated amount of carbon contained within the above and below ground cover crop biomass.

Table 3. 2. Cumulative N_2O-N and CO_2-C emissions, soil temperature and moisture in 2019 and 2020 during cover crop decomposition.

Cover crop	Year	N_2O-N	CO_2-C	Soil Temp	Soil Moist
		g ha^{-1}	kg ha^{-1}	^oC	cm^3 cm^{-3}
No-cover crop	2019	301	3935	17.19	0.32
Cover crop	2019	537	5093	13.02	0.33
No-cover crop	2020	359	5691	17.93	0.22
Cover crop	2020	955	7969	15.89	0.3
p-value		0.1	0.41	0.41	0.07
2019		419	4518	12.4	0.34
2020		657	6829	16.95	0.27
p-value		0.003	0.001	0.03	<0.001
No-cover crop		330	4813	17.32	0.26
Cover crop		746	6531	14.21	0.32
p-value		<0.001	0.004	0.05	<0.001

In 2020, CO_2-C emissions during the growth phase were similar in the cover crop and no cover crop treatments and averaged 1500 kg CO_2-C ha^{-1} (Reicks et al. 2021). However, during decomposition, CO_2-C emissions in the cover crop and no-cover crop treatments were 7970 and 5690 kg CO_2-C ha^{-1}. The difference between CO_2-C emitted in the cover crop and no-cover crop treatment was equivalent to 69% of the estimated amount of above and below ground cover crop biomass-C. The increased CO_2-C emissions were attributed to the cover crop providing organic C to the soil which was subsequently mineralized (Poeplau and Don, 2015; Rosecrance et al., 2000; Aulakh et al., 2001; Smith et al., 2011). Lower emissions in 2019 than 2020 were attributed to cooler temperatures.

In 2019, CO_2-C emissions tended to decrease as the season progressed, whereas in 2020 CO_2-C increased or remained relatively constant and then decreased after September 15 (Figure 3.2). In both years, the ratio between CO_2-C and N_2O-N varied across the seasons. Since the CO_2-C is a function of the aerobic respiration and N_2O-N emission is a function of both nitrification and anaerobic respiration, a higher CO_2-C/ N_2O-N ratio suggests that there was an increased importance of aerobic respiration or a change in the soil microbial community structure. For example, from June 24 to September 10, 2019, the ratio between CO_2-C and N_2O-N in the cover crop and no-cover crop treatments were 10,500 and 16,500 (kg CO_2-C h^{-1}) (kg N_2O-C ha^{-1})$^{-1}$, respectively (p=0.006). This apparent cover-crop induced decrease in the CO_2-C and N_2O-N ratio suggests that the biota in cover-crop treatment has a higher reliance on anerobic respiration than the no-cover crop treatment. This apparent increased reliance on anaerobic respiration was associated with increased CO_2 emissions, which most likely reduced soil O_2 concentrations.

Between September 11 and October 20, 2019, similar results were observed and the CO_2-C to N_2O-N ratios in the cover crop and no-cover crop were 3940 and 5905 (kg CO_2-C h^{-1}) (kg N_2O-C ha^{-1})$^{-1}$ (p=0.08), respectively. Again, these results suggest that the cover crop treatment had a higher reliance on anaerobic respiration than the no-cover crop treatment.

In 2020, between June 24 and September 10 the CO_2-C to N_2O-N ratio in the cover crop and no-cover crop treatment were 7,720 and 15,970 kg CO_2-C h^{-1}) (kg N_2O-C ha^{-1})$^{-1}$, respectively (p=0.004). Later in the season (September 11 to October 20) the CO_2-C to N_2O-N emissions ratios were similar in the cover crop and no-cover crop treatment and had a ratio of 14,980 (kg CO_2-C h^{-1}) (kg N_2O-C ha^{-1})$^{-1}$. Temporal changes in the CO_2-C to N_2O-N ratio for this same soil were also observed by Thies et al. (2020), where the impact of different fertilizer application dates on N_2O-N and CO_2-C emissions were investigated. It was observed that fertilizer applied on 20 September 2017 had a CO_2-C to N_2O-N ratio of 1360 whereas fertilizer applied on 1 October 2017 had a ratio of 24,000. These values suggest that the relative amount of N_2O-N that is emitted per unit or respired CO_2-C can vary widely.

Change in soil total inorganic nitrogen and carbon during decomposition

In the linked experiment, Reicks et al. (2021) reported that the cover crop reduced soil inorganic N and soil moisture during the cover crop growth phase compared to no cover crop treatment. However, when the chambers were moved to a new location slightly different results were observed. At the new location, the amount of NO_3 + NH_4-N contained in the surface 30 cm at cover crop termination was not affected by the cover crop. However, at harvest the cover crop increased the amount of inorganic N in the soil (Table 3.3). These results suggest that N mineralization of the cover crop biomass may provide N to corn. However, the timing of the mineralization is critical to assess if it will reduce the N requirement in the current or future crop. In this example, an increase of 14 kg N ha^{-1} was observed following harvest.

An increase in N at harvest would not reduce the N requirement in the harvested crop, however it might influence the N requirement in the upcoming crop if the N remains in the soil profile. In the past, fertilizer replacement values for cover crops in corn have been mixed. According to Mahama et al. (2016), the N fertilizer requirement in the cash crop can be reduced by introducing legume cover crops. However, different results have been reported for non-legume cover crops. Sawyer et al. (2017) reported that the rye cover crop reduced corn yield by 5% in Iowa and that the economic optimum N rate for corn were similar in the rye cover crop and no-cover crop treatments. Pantoja et al. (2016) extended this discussion and reported that the rye cover crop does not provide a meaningful amount of N to the growing corn plant in the year of termination. However, neither study considers what happens in following years.

The amount of soil organic C contained in the surface 30 cm at V4 growth stage of corn (cover crop termination) was not affected by cover crop in either 2019 or 2020. However, when the experiment was terminated in October the cover crop increased the amount of soil organic carbon 3,031 kg SOC-C ha^{-1}. This increase in SOC indicates that a relatively large portion of the cover crop biomass remained in the soil after 117 to 119 days of decomposition.

Table 3. 3. Cover crop impact on soil inorganic nitrogen (NO_3 + NH_4) and organic C contained in the surfaced 30 cm at cover crop termination and following harvest in 2019 and 2020. Difference in lowercase letters indicate significant different in mean at p = 0.05.

		Total inorganic N		Total organic C	
Treatment	Year	Cover Crop Termination	Following Harvest	Cover Crop Termination	Following Harvest
		-------------------kg ha^{-1}---------------			
No-cover crop	2019	48	36 a	79,910	81,290
Cover crop	2019	42	42 a	81,280	84,870
No-cover crop	2020	38	50 a	74,790	75,280
Cover crop	2020	48	73 b	71,340	77,760
p-value		0.1	0.05	0.24	0.58
2019		45	39	80,600	83,080
2020		40	46	73,060	76,520
p-value		0.9	<0.001	0.01	0.001
No-cover crop		43	43	77,350	78,290
Cover crop		45	58	77,810	81,320
p-value		0.7	0.004	0.8	0.05

Change in the soil microbial biomass due to cover crop decomposition

Microbial biomass was higher when the cover crop was termination than following harvest and it was higher in the cover crop than the no-cover crop (Table 3.4). These temporal differences were consistent with Kaiser et al. (1995) where it was reported that microbial biomass was generally lowest during the winter and highest in the summer. Across years, the fungi concentration was lower than the bacteria concentration. In 2019, the fungi to bacteria ratio was higher in the cover crop than the no-cover crop treatment at both sampling dates. For example, at cover crop termination the ratio was 0.44 in the cover crop and 0.24 in no cover (p=0.01). Similarly, following harvest the fungi to bacteria ratio was 0.29 for the cover crop treatment and 0.18 for the no-cover crop treatments (p=0.06). Apparent relative cover crop induced increases in fungi may be associated with the composition of the cover crop biomass, cooler soil temperatures, and higher soil moisture contents. Our observations were consistent with Malik et al. (2016), where it was reported that following litter addition there was an increase in fungal phyla.

Table 3. 4. The impact of the cover crop on total biomass, bacteria, and fungi at cover crop termination and following harvest in 2019 and 2020. Difference in lowercase letters indicate significant different at p = 0.05.

		Total biomass		Total Bacteria		Total Fungi	
Treatment	Year	Cover Crop Termination	Following Harvest	Cover Crop Termination	Following Harvest	Cover Crop Terminatio n	Following Harvest
		-------------------------------mg C (kg soil)$^{-1}$ ----------------------------------					
No-cover crop	2019	4.7 a	1.4	2.3	0.8	0.5 a	0.1
Cover crop	2019	8.5 b	2.5	2.9	1.2	1.3 b	0.4
No-cover crop	2020	3.2 a	1.7	1.4	1.0	0.3 a	0.2
Cover crop	2020	4.6 a	2.7	2.1	1.3	0.4 a	0.4
p-value		0.03	0.9	0.98	0.56	0.01	0.8
2019		6.5	1.95	2.6	1.05	0.9	0.25
2020		3.9	2.2	1.75	1.15	0.35	0.3
p-value		<0.001	0.25	0.001	0.09	<0.001	0.4
No-cover crop		3.95	1.55	1.85	0.9	0.4	0.15
Cover crop		6.55	2.6	2.5	1.25	0.85	0.4
p-value		<0.001	0.004	0.005	0.001	0.001	0.030

Associated with the higher fungus to bacteria ratio in the cover crop than the no-cover crop treatment was higher CO_2-C to N_2O-N emission ratios. Changes in the microbial community structure are important because there are fundamental differences between fungi and bacteria. These differences include that: 1) fungi decompose more complex organic molecules than bacteria, 2) fungi have slower growth rates than bacteria, and 3) fungi may store more carbon in the soil than bacteria (Helfrich et al., 2015).

In 2020 slightly different results were observed and the fungi to bacteria ratios were similar in cover crop and no cover crop treatment. In addition, the fungi to bacteria ratios were similar (p=0.18) at both sampling dates (Table 3.4). These finding suggest that cover crops in addition to reducing soil temperature and increasing soil moistures, have the potential to change the microbial community structure, which in turn can affect the relative amount of N_2O-N and CO_2-C that is emitted.

Partial Carbon Dioxide Equivalence (CO_{2e})

Rye cover crops have mixed results on N_2O-N and CO_2-C emission over the entire year. Our investigation found that during the cover crop growing phase, rye lowered soil moisture and inorganic nitrogen, and reduced N_2O-N emissions by 66% relative to no-cover crop. Different results were observed during the decomposition phase, when the cover crop increased N_2O-N and CO_2-C emissions. The increase in emissions during decomposition may be related to the cover crop providing organic carbon as well as lowering the soil temperature and increasing the soil moisture. When combing both phases, the rye cover crop did not influence (p=0.71) N_2O-N emissions and were 565 g N_2O-N ha^{-1} in the rye cover crop and 530 g N_2O-N ha^{-1} in the no-cover crop treatment. This finding suggests that reduced N_2O-N emission during cover crop growing phase offsets the increased emission during decomposition. However, the cover crop had greater (p-value= 0.001) CO_2-C emission (6750 kg CO_2-C ha^{-1}) than the no cover crop treatment (5951 kg CO_2-C ha^{-1}). This increase does not account for the large amount of CO_2 removed from the atmosphere by the cover crop. The partial CO_{2e} was determined by considering CO_2-C and N_2O-N emissions and the amount of CO_2-C that was removed from the atmosphere during photosynthesis. In the cover crop and no cover crop treatment the average CO_{2e} across years and the entire cover and cash crop growth cycles were -1,061 and 496 kg CO_{2e} ha^{-1}, respectively. These values suggest that cover crops have the potential to reduce the agricultural carbon footprint.

N_2O-N and CO_2-C emission prediction using a machine learning algorithm

Correlation analysis across years and treatments showed that the daily N_2O-N emissions were positively correlated to CO_2-C, air temperature, soil moisture, soil temperature, cover crop-C remaining in the soil, and rainfall (Figure 3.3). Similarity, analysis showed that daily CO_2-C emissions were positively correlated to N_2O, air temperature, soil moisture, soil temperature and cover crop-C remaining in the soil. However, CO_2-C emissions and rainfall were not correlated.

After determining which input parameters were statistically related to the N_2O-N and CO_2-C emissions, models based on soil temperature, air temperature, soil moisture, amount of cover crop-C remaining, and rainfall were developed. The RF model that predicted daily N_2O-N and CO_2-C emissions over two years outperformed all models and had with highest R^2, lowest RMSE and MAE during training and validation (Table 3. 5). These findings were consistent with Philibert et al. (2013), Hamrani et al. (2020), and Saha et al. (2021).

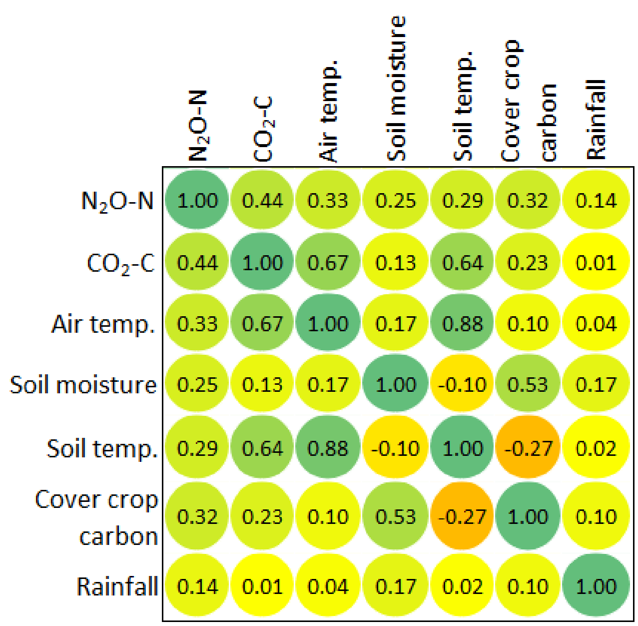
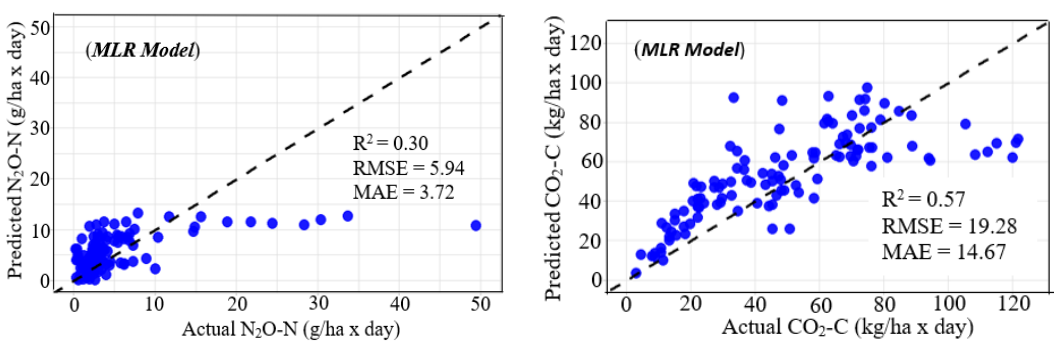


Figure 3. 3. Correlation matrix between the different daily measurements in 2019 and 2020 (n=480). All correlation values (either negative or positive) equal or above 0.25 are statistically significant at $p<0.001$, between 0.13 to 0.17 are statistically significant at $p=0.05$ and values below 0.13 are not statistically significant. Positive values indicate positive relation whereas negative is just reverse.

Table 3. 5 Performance comparisons during training and validation for a traditional regression-based model (MLR) and machine learning (PLSR, SVM, RF and ANN) models for predicting N_2O-N and CO_2-C emission.

N_2O-N	Training dataset			Validation dataset		
Models	R^2	RMSE	MAE	R^2	RMSE	MAE
MLR	0.26	6.41	3.61	0.30	5.94	3.72
PLSR	0.23	6.52	3.78	0.28	6.03	3.97
SVM	0.69	4.61	0.95	0.60	4.69	2.24
RF	**0.95**	**1.85**	**0.92**	**0.73**	**3.71**	**2.08**
ANN	0.56	5.56	2.87	0.61	4.67	2.27
CO_2-C	Training dataset			Validation dataset		
Models	R^2	RMSE	MAE	R^2	RMSE	MAE
MLR	0.60	17.86	13.96	0.57	19.28	14.67
PLSR	0.56	18.8	14.68	0.55	19.91	15.06
SVM	0.81	12.6	8.51	0.73	15.47	10.05
RF	**0.96**	**5.71**	**4.05**	**0.85**	**11.92**	**8.55**
ANN	0.69	16.07	12.44	0.68	16.18	10.65



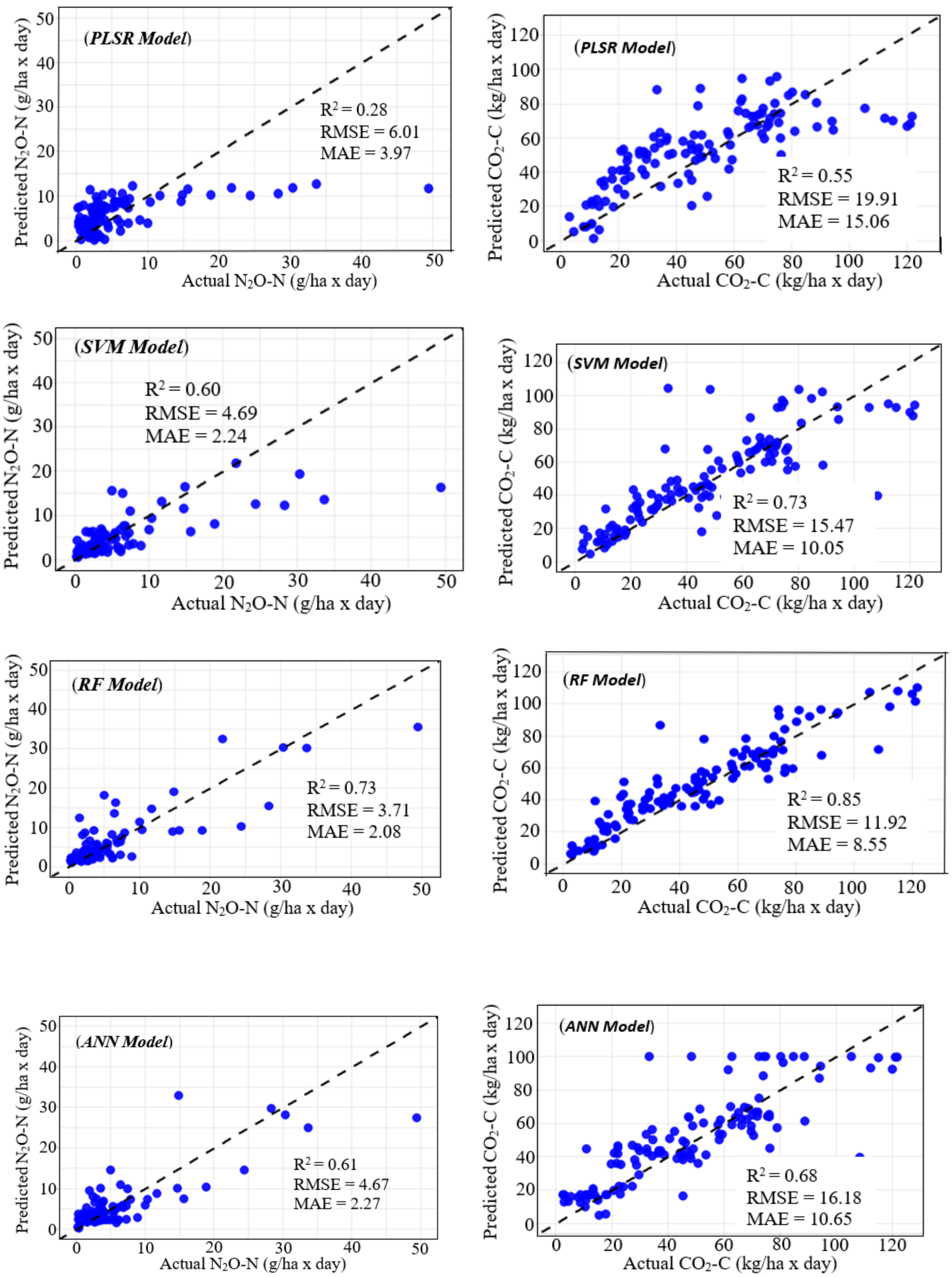


Figure 3. 4. Validation of the actual vs. predicted N_2O-N and CO_2-C emissions using MLR, PLSR, SVM, RF and ANN models.

During training, the RF model explained 95% of the N_2O-N emissions variability in the cover crop and no-cover crop treatments over two years. The RMSE and MAE for this model was 1.85 g N_2O-N ha^{-1} and 0.92 g N_2O-N ha^{-1}. For the validation data set, the R^2, RMSE and MAE values were 0.73, 3.7 g N_2O-N ha^{-1} and 2.1 g N_2O-N ha^{-1} respectively. The MLR, PLSR, SVM, and ANN models did not perform as well as the RF model (Figure 1.4.).

The importance of the variables was determined for each model (Figure 3.5). In this analysis, variables were assigned scaled score between 0 to 100, with 100 being most important and 0 being least important. Variable importance differed among models and between the two emission gasses. For the N_2O-N RF model, cover crop carbon was most important variable followed by air temperature, soil temperature, soil moisture and lastly rainfall. For the CO_2-C RF model, soil temperature was the most important variable, and rainfall was the least important.

Models such as these can be used to improve our understanding of the factors affecting emissions and provide insights into how to minimize CO_2-C and N_2O-N emissions. For example, decreasing the soil temperature 1^{o} C reduced RF N_2O emissions predictions by 0.52%. Similar analysis can be conducted to predict how changes in soil moisture or cover crop biomass would affect emissions. This analysis suggests that additional research is needed to extend the use of the N_2O-N and CO_2-C machine learning algorithms to assess different climate and management scenarios (McLennon et al., 2021).

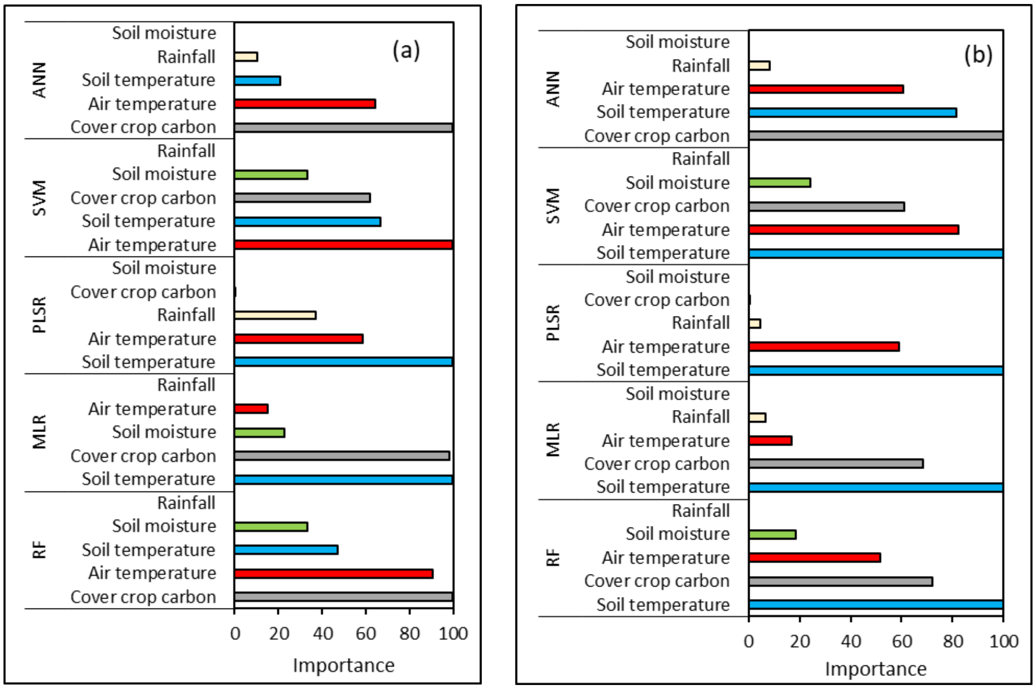


Figure 3. 5. Relative importance of each variable used to model N_2O-N (a) and CO_2-C (b) emissions. Scaled importance score (0 to 100) was generated and higher scores indicate that the variable is of greater importance in the model.

Conclusions

The decomposing rye cover crop stimulated microbial activity and changed the microbial community structure, which in turn increased N_2O-N and CO_2-C emissions. During cover crop decomposition, the amount of N_2O-N that that was emitted was equivalent to 0.24 and 0.42% of the N contained in the above ground cover crop biomass in 2019 and 2020 and an amount that was equivalent to 39% and 76 % of cover crop-C was released as CO_2-C in 2019 and 2020, respectively. Furthermore, the cover crop increased soil total carbon, total inorganic nitrogen, and moisture, all of which promote soil metabolic activity and respiration. During the rye cover crop growing phase, it reduced the N_2O-N emission which was attributed to nutrient and moisture uptake by the rye. This means that the cover crops had opposite effects on GHG emissions during growth and decomposition. For this reason, measuring cover crop emissions over the whole growing season is essential to fully understand their emission pattern.

Analysis suggests that only a relatively small portion of the N contained in the cover crop was contained in the soil at harvest or emitted into the atmosphere as N_2O-N. Although the cover crop increased N_2O-N and CO_2-C emissions, it also released inorganic nitrogen into the soil. This increased N contained in the soil at harvest has the potential to reduce the crop plants nutrient requirement in subsequent years. These results suggest that the mineralization of N from the rye biomass and N uptake by the growing corn plant were not synchronized. This question will be considered in subsequent papers. In the cover crop and no cover crop treatments the average CO_{2e} across years was -1,061 and 496 kg CO_{2e} ha^{-1}, respectively. These values suggest that cover crops have the potential to reduce the agricultural carbon footprint.

Additionally, our results demonstrate that ML based algorithm may can be useful for predicting N_2O-N and CO_2-C emission. Of the models tested, the Random Forest explained the most amount of variability over two seasons. Additionally, our results suggest that we may be able to improve GHG predictions by merging machine learning and process-based models into a common analysis. Models such as these, can be used to predict the effects of different management systems and climatic conditions on N_2O and CO_2 emissions.

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Dissertation Conclusions

Our results demonstrate that ML based algorithm may can be useful for predicting N_2O-N and CO_2-C emission. Of the models tested, the Random Forest explained the most amount of variability over two seasons. Similarly decomposing rye cover crop stimulated microbial activity and changed the microbial community structure, which in turn increased N_2O-N and CO_2-C emissions. During cover crop decomposition, the amount of N_2O-N that that was emitted was equivalent to 0.24 and 0.42% of the N contained in the above ground cover crop biomass in 2019 and 2020 and an amount that was equivalent to 39% and 76 % of cover crop-C was released as CO_2-C in 2019 and 2020, respectively. Furthermore, the cover crop increased soil total carbon, total inorganic nitrogen, and moisture, all of which promote soil metabolic activity and respiration. During the rye cover crop growing phase, it reduced the N_2O-N emission which was attributed to nutrient and moisture uptake by the rye. This means that the cover crops had opposite effects on GHG emissions during growth and decomposition. For this reason, measuring cover crop emissions over the whole growing season is essential to fully understand their emission pattern.

Our second study using meta-analysis suggest that globally, using a cover crop in a corn production system increased SOC by 7.8%. SOC storage was positively correlated with cover crop biomass and temperature and negatively correlated with SOC_i. The negative correlation between initial SOC (SOCi) and carbon storage is consistent with first order kinetics (Joshi et al., 2020). In this analysis, percent carbon increases were highest in systems that used legume cover crops and no-tillage. Current corn fields with cover crops that have a SOC sequestration rate of 0.8 Mg (ha × year)$^{-1}$ are sequestering 4.98 Mg of

SOC-C year^{-1} in the United States and 159.2 million Mg SOC year^{-1} globally. If all US corn fields used cover crops, 29.12 million Mg SOC year^{-1} could be sequestered annually, which would result in a CO_{2e} value of 107 million metric tons of carbon dioxide. These findings imply that in cover crops induced increases in SOC can improve soil health and the soils yield potential. Higher yield potential may be responsible for the cover crop induced yield increases. Finding from this study can be used to create regression models with the greatest potential to sequester carbon. However, these models may be limited in scope because many studies do not report important information. After conducting worldwide meta-analysis, we found that growing cover crops on cropland rather than leaving it in a fallow phase improves SOC stock and serves as an effective approach to mitigate for anthropogenic greenhouse gas emissions.

Lastly based on historical climate data of Nepal, which include 116 years since 1901, has shown an increasing trend for average temperature by 0.016 ^{o}C yr^{-1} whereas precipitation has shown a decreasing trend by 0.137 mm yr^{-1}. Such weather trends could enhance glacier melt associated flooding, and delayed monsoon rainfalls negatively impacting the agricultural production. In this context of changing climate CA can play important role to resilience to the impact of climate change. The CA involves a combination of production technologies to attain high yield on existing land to meet the domestic and global food demands with minimal environmental impacts. Evaluation of various aspects of CA revealed benefits by minimizing soil disturbance, soil erosion, and pest pressure, and by increasing SOM and aggregate stability. These effects are more pronounced in degraded soils. The benefits of CA documented from Nepal has shown promise especially in the mountain agroecosystem which faces sustainability challenges due to steep and fragile topography and rapid climate change. Implementing region-specific CA adaptation strategies and working closely with farmers to identify a suitable conservation tool will minimize climate change-associated risk and uncertainties in food production. Some model assessment suggests an increased yield of selected crops with a moderate rise in temperature and increased precipitation. Identifying those crops and developing a conservation management strategy will address both challenges, food security and climate change.

Future Recommendations

Our results suggest that we may be able to improve GHG predictions by merging machine learning and process-based models into a common analysis. Models such as these, can be used to predict the effects of different management systems and climatic conditions on N_2O and CO_2 emissions.

Moreover, this dissertation study found that even with all the advantages, there are still many challenges to CA adoption in developing countries like Nepal, where most farmers lack financial capital, and continue to practice traditional subsistence farming on small field parcels. Resource-poor farmers cannot easily cope with associated yield loss during the early years of transition to CA practice. Thus, governmental policies are needed to support farmers and provide economic incentives through crop insurance or subsidies in the agricultural inputs, at least during the initial years of the CA practicing. The government needs to prioritize and promote low-cost technologies that can be used effectively in difficult terrains.