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Addressing Soil Carbon Sequestration Response from Multispecies Dairy Forage Systems and Modeling Rangeland Beef Cow Dry Matter Intake Using Precision Enteric Emissions Measurements

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BY

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THESIS ACCEPTANCE PAGE

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis 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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This thesis is dedicated to my family. You have all helped me along with this journey from helping instill a love for agriculture in my heart, helping me through my education, and always standing in my corner and for that I am forever grateful.

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ABSTRACT

ADDRESSING SOIL CARBON SEQUESTRATION RESPONSE FROM MULTISPECIES DAIRY FORAGE SYSTEMS AND MODELING RANGELAND BEEF COW DRY MATTER INTAKE USING PRECISION ENTERIC EMISSIONS MEASUREMENTS

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Regenerative agriculture is a pressing matter for the dairy industry to address cropland sustainability and carbon sequestration. One regenerative management practice that has been identified to help with row crop sustainability for key metrics like soil organic carbon (SOC) is complex covers. When producers use complex covers one of the main challenges is that it takes time to detect a change in SOC. However, simulation models are a tool that can be used to help determine if a regenerative practice is a strategy that gives the best results (i.e., increased SOC) while aligning with long-term production goals. Therefore, our objectives were to 1) modify the DAYCENT model to simulate soil carbon and flux with complex cover practices and 2) simulate different conventional and regenerative cropping scenarios on United States dairy farms in Wisconsin and Michigan to assess differences in soil carbon (C). The Soil Carbon CareTaker model used parameters from DAYCENT that were modified to estimate SOC with different complex cover and tillage practices over 30 years for dairy fields (n = 12) within Michigan. The calibrated model was shown to lack precision (R^2 = 0.07) but was highly accurate [mean bias = -0.26 (MB)]. We simulated a base case for each field along with four different scenarios: no-till (NoTill), 30 years of continuous corn (CornOnly), cover crops with

tillage (CC), and cover crops with no-till (CC NoTill). The Michigan dairy fields were split into three different regions: west (n = 4), central (n = 2), and east (n = 6). Within these regions, we observed an average least percent soil C change from the base case of -14% (west), -12% (central), and -15% (east) from the CornOnly scenario, while the greatest average percent change from the base for each region was 350% (west), 361% (central), and 278% (east) for the CC NoTill scenario. Thus, the Soil Carbon CareTaker model can be used as a tool for producers to assess regenerative management strategies that will enhance C sequestration, meet sustainability goals, and provide cost-effective regenerative dairy products to meet shifting consumer demands.

Another goal for sustainable agriculture is assessing range cattle dry matter intake (DMI). DMI is an essential component to determining nutrient supply and for evaluating grazing management. Not only is DMI a major concern for cattle management, but it is also a key component regarding the rising pressure to assess the impact of enteric gas emissions from cattle on the environment. Since DMI and enteric emissions are directly correlated, this provides a potential to leverage enteric emissions to predict DMI. Obtaining data for beef cattle DMI and enteric emissions on forage-based diets similar to extensive rangelands is needed to develop an equation capable of predicting DMI for grazing cattle. Therefore, our objectives were to: 1) measure CH_4, CO_2, and O_2 emissions, and DMI of dry beef cows and 2) use these data to develop a mathematical model capable of predicting grazing DMI. The predictive equation or precision system model (PSM) was developed using data from two feeding trials that were conducted using technology to measure enteric emissions (GreenFeed™), daily DMI (SmartFeed Pro™), and front-end body weights (SmartScale™). This study was conducted in western

South Dakota during the winter of 2022. Two feeding trials used non-lactating beef cows (n = 7) receiving low (6% CP) or moderate (15% CP) quality grass hay using a 14-day adaptation period and a 14-day data collection period. Average CH_4 (g/day), CO_2 (g/day), and O_2 (g/day) were 265 $\pm$ 8.78, 7,953 $\pm$ 228.83, 5,690 $\pm$ 1,488.19, for the low and 215 $\pm$ 13.63, 6,863 $\pm$ 393.79, 5,244 $\pm$ 328.32 for the moderate treatments, respectively. The PSM was evaluated for accuracy [mean bias (MB)] and precision (R^2). Initial models were less than desirable for individual DMI with a range of R^2 of 0.01- 0.36 for single and multiple linear regression. Using herd-level data and a 3-day smoothing, the CH_4 model produced the best results with an R^2 and MB of 0.91 and -255.00, respectively. A major limitation was poor GreenFeed™ use rates resulting in a limited sample size to compare with individual daily DMI data. Advances in DMI estimates for grazing cattle will have the potential to enhance stocking rate estimates, supplementation, and individual animal efficiency, leading to lower cost, optimized resources, and enhanced environmental sustainability.

CHAPTER 1. LITERATURE REVIEW

Background of United States Cropping Systems

In the United States, agronomic production systems are severely degraded by conventional farming practices, overgrazed rangeland, and the lack of knowledge regarding soil management (Pittelkow et al., 2015). The rapid evolution of modern farming practices and technology has removed labor barriers, making it economically rewarding to convert native rangelands into row-crop production (Turner et al., 2018). Land conversion to row-crop agriculture increased changes in hydrological patterns through soil erosion, causing a decrease in water quality via eutrophication and increased sediment load in streams and rivers (Bielders et al., 2003; Helmers et al., 2012). Erosion happens naturally from water and wind-breaking up and moving soil particles. Although erosion is natural, soil management can increase or decrease erosion rates (t/ha) (Telles et al., 2011). An estimated 75 billion tons of topsoil are lost annually, which causes an economic loss of ~44 billion dollars (Pimentel et al., 1995; Pimentel, 2000). Another issue is when soil-bound or dissolved reactive phosphorus (P) accumulates in waterways from excessive fertilization. The excess P enters water sources from erosion, leaching, and artificial drainage, causing eutrophication. Eutrophication is when water bodies get an increased amount of minerals, mostly P, that increase algal growth, which depletes water of species diversity. The decline in species is due to increased consumer species, toxic blooms of algal, and oxygen depletion (Smith and Schindler, 2009). Eutrophication can be detrimental to aquatic plant communities, fish, livestock, and even humans (Smith and Schindler, 2009). Loss of soil productivity from degradation results in decreased crop production, increased erosion, and eutrophication of waterways (Menendez et al., 2020), ultimately affecting humans who rely on soil for food, animal feed, and fiber, all products essential for human life.

Importance of Cropping to the Midwest

The midwestern region of the United States contains over 362,315,055 ha dedicated to growing crops (USDA, 2022). Within states such as South Dakota (SD), Wisconsin (WI), Michigan (MI), and Minnesota (MN), there are 5,309,475, 10,234,499, 1,126,442, and 6,984,874 hectares, respectively, dedicated to growing corn (*Zea mays*), soybean (*Glycine max*), and spring/winter wheat (*Triticum aestivum L.*) (USDA, 2021). Since these areas produce a large portion of the United States' crops, ensuring their long-term productivity and sustainability is crucial. Regenerative agriculture provides practices that help reduce environmental impacts such as erosion and eutrophication by building healthier soil that requires less fertilizer, is not susceptible to erosion, and improves crop production. This is a systemic fix compared to practices like buffer strips that only reduce the unintended consequences of conventional farming (e.g., runoff).

Five Principals of Regenerative Agriculture

Lal (2020) indicated that there are five principles to regenerative agriculture which are 1) soil cover, 2) crop diversity, 3) living roots, 4) reduced soil disturbance, and 5) livestock integration. The first is soil cover which is essential for protecting the soil surface and regulating soil temperature. Crop diversity is used to increase soil buffering capacity and ecosystem resilience/vigor. Lal (2020) stated the third is keeping a living root in the soil to help keep the integrity of the soil and they are a pathway for atmospheric carbon (C) to be stored in the soil. Roots also feed microbes which help build soil aggregates and increase water infiltration by decreasing soil compaction. The fourth principle is reducing soil disturbances which improves soil integrity by maintaining soil structure. Many soil disturbances, such as conventional tillage, reduce water absorption and the ability of plants to hold soil in place. Lastly, livestock integration promotes plant growth by thinning out biomass and promoting nutrient cycling of plants, such as cover crops or plant residues like corn stubble by grazing, trampling, and deposition of manure. Manure is a natural fertilizer produced by livestock and helps attract insects known as detritivores that aerate the soil and break down organic matter (OM; Lal, 2020).

Soil Health

Soil health has been defined as the "capacity of soil to function as a vital living system to sustain biological productivity, maintain environmental quality, and promote plant, animal, and human health" (Doran, 1996; Doran and Zeiss, 2000). When soil organic matter (SOM) increases, it improves crop production while increasing soil organic carbon (SOC; approximately 58% of SOM). Soil OM is all organic soil materials except charcoal, non-decayed plants, animal tissues, and living biomass (Stevenson, 1994; Oades, 1988; Fig. 1). For a 1% increase in SOM, there is a possibility for an additional 60,567 L/ha of soil water holding capacity (Overstreet, 2009; Sullivan, 2000). Further, it has been found that crop yields are 1.2 times higher for SOC at 1% compared to 0.5% but then level off once SOC reaches 2.0% (Oldfield et al., 2019). Crop yields for maize and wheat have the potential to increase by 10% $\pm$ 11% and 23% $\pm$ 37%, respectively, with increased SOM content (Oldfield et al., 2019). Complex covers provide a potential regenerative production strategy to improve SOM and SOC (Lu et al., 2000). For the current study, we defined multispecies cover crops and interseeded crops as "*complex covers*," which are not the primary crop planted and are used for ground cover and other benefits.

Complex Covers

Nurse crops are planted with cash crops to help shelter and protect from weeds and undesirable plants. Alfalfa (*Medicago sativa*) is commonly planted with an annual plant like oats (*Avena sativa*) and peas (*Pisum sativum*) to suppress weeds and then will be harvested together for increased biomass. It is shown that nurse crops increased dry matter yield, suppressed weeds, and did not affect the quality of forage in the seeding year when compared to an alfalfa field planted without a nurse crop (Hall et al., 1995). However, nurse crops have been shown to restrict alfalfa growth in years with below-average precipitation (Hall et al., 1995). Since alfalfa is a perennial, using it for a cover crop is not a popular option for many producers, but it is commonly interseeded with other crops. An example of this is a producer planting a forage grass mix such as tall fescue (*Festuca arnudinacea*), timothy grass (*Phleum pratense*), and meadow fescue (*Festuca pratensis*) to improve yield, persistence, and nutrients in their alfalfa hay crop.

Cover crops are defined as crops grown to protect the soil when no cash crops (i.e., primary crops such as corn) are grown (SWCS-U.S., 1994). Cover crops can benefit producers by protecting soil from wind and water soil erosion, improving organic C, water infiltration, and reducing nutrient leaching (SWCS- U.S.,1994). For example, Franzlubbers et al. (2021) demonstrated that cover crops increased cumulative C mineralization by 9% when multispecies cover crops were planted, compared to no cover crops (control). They also found that particulate organic C and particulate organic nitrogen were increased by 4% and 5%, respectively, when multispecies cover crops were compared to the control (Franzluebbers et al., 2021). Although cover crops are generally used to improve soil health, they can also be used for many other factors, such as wildlife habitat, extending the winter grazing period for cattle, and preventing weed growth. Legume cover crops can add extra nitrogen (N) to the soil through symbiotic N fixation (Mylona et al., 1995). Symbiotic N fixation is the relationship between soil bacteria that bind to the root hairs of the legume plant. The soil bacteria synthesize nitrogenase to reduce inorganic N making it available for plant uptake (Mylona et al., 1995). Nitrogen-fixing plants like alfalfa can fix 140 kg N/ha/year (Hardy et al., 1968). Interseeding crops is another technique that producers can use to establish cover while the primary crop is still growing (Youngerman et al., 2018). Many benefits come from intercropping; some include reduced nitrate (NO^{-3}) leaching, increased growing period by establishing growth earlier in the season, and maximized biomass cover. Although complex covers protect the soil that is typically exposed, they also work to make the soil healthier. Nutrients for plant growth are kept in the ground, along with being the home for many microbes that can help or destroy the plant's roots below. Soil microbes and fungi cycle C, N, and P by transforming minerals in the soil through the processes of nitrification and denitrification (Aislabie and Deslippe, 2013). Nitrification is the oxidation of reduced forms of N to nitrite (NO^{-2}) and NO^{-3}. It links natural, industrial, and agricultural systems to the N cycle (Ward, 2018).

On the contrary, denitrification is the reduction of aerobic bacteria by one or both ionic N oxides to gaseous oxides (Knowles, 1982). Denitrifiers recycle waste and detoxify soils with mineralization and immobilization (Aislabie and Deslippe, 2013). Nitrogen, P, and potassium (K) are the most important macronutrients for plant growth. The growth of plant leaves and stems is influenced by N and P, which affects root growth and the blossoming of fruit/flowers. Lastly, K is an aide for the overall function of the plant (e.g., nutrient transport in plant tissue). Nitrogen, P, and K are common fertilizers used in cash crop operations (Malghani et al., 2010). Many years of N application can negatively affect the N cycling microbes, such as the nitrifiers and denitrifiers (Shen et al., 2008; Hallin et al., 2009). Long-term N-P-K fertilizer in grasslands was shown to affect different species of microbes present in the soil but did not affect the overall or bacterial species function of those microbes (Pan et al., 2014). However, few studies have evaluated the effects on microbes from continuous P and K fertilizer use (Pan et al., 2014).

Microbial populations also affect soil C dynamics (Parton et al., 1987). Concerns caused by climate change have increased interest in C mitigation and sequestration strategies among row-crop producers, who are at the forefront of the efforts in agricultural supply chains. Keeping C in the soil reduces the amount of carbon dioxide (CO_2) released into the atmosphere (Pan et al., 2014). Regarding function, soil C is a significant factor for water purification, maintaining soil health, and increasing crop yields. Many traditional farming practices, such as tilling/plowing, release stored soil C into the atmosphere, changing the land from a C sink to a C source. Not only does conventional tilling release soil C, but it also leaves it bare and susceptible to erosion and nutrient loss. Conventional tillage is when a producer uses equipment such as a plow or disk to turn up the soil and directly plants seeds into open soil (Claassen et al., 2018).

Conservation tillage, commonly known as "no-till," is growing crops without traditional tillage practices. It uses equipment designed to cut through residue so the seed can be planted directly into the residue mulch. In doing this, no-till retains surface residue to prevent erosion, limits evaporation, suppresses the growth of weeds, and improves water infiltration. The no-till method retains at least 90% of crop residue compared to conventional practices, retaining 10-75% of residue depending on the plow or disk (Claassen et al., 2018). However, increased soil residue does have negative consequences that can impede agronomic production, such as delayed germination from soil cover reflecting sunlight (high albedo) compared to freshly tilled black soils that more readily absorb solar radiation. Excess residue may also increase water retention in fields beyond field capacity, again slowing agronomic activities like planting due to excessively moist soils.

Despite these negative consequences, cover crops and no-till practices can help increase the nutrients a producer can keep in the soil, enhancing residue cycling from cover crops, reducing fertilizer requirements and the amount of excess nutrients that enter our water sources from leaching (Lal et al., 2004). In turn, soil fertility is improved because more nutrients become available to the plant in the soil solution. Soil solution is a saturated solution containing disbanded matter from soil chemical and biochemical processes and transactions with the hydrosphere and biosphere (e.g., inorganic phosphorus; Freeze and Cherry, 1979). The hydrosphere is a "discontinuous layer of water at or near Earth's surface. It includes all liquid and frozen surface water, groundwater held in soil and rock, and atmospheric water vapor." (Britannica, 2021). The biosphere is a thin layer that supports life on Earth, extending from the bottom of the ocean into the atmosphere and is composed of living and nonliving organisms (Gates et al., 2022). Although there are many noted benefits from using cover crops, their establishment and management can be challenging, ultimately limiting adoption.

Cover Crop Management

To establish cover crops, producers need to select their cover crop mixes, planting dates, and seeding rates to ensure they are synonymous with the cropping system and soils for each farming operation (NRCS, 2011). A primary example is planting clovers, which typically need a higher pH to establish and grow. Producers also need to set a clear goal for how they want to improve their soil. They must also identify seed planting depth requirements to avoid planting small seeds too deep or large seeds too close to the surface for adequate germination (NRCS, 2011).

Many methods to implement cover crops include broadcasting, interseeding, drilling, frost/dormant seeding, manure slurry seeding, and aerial seeding. More novel seeding applications include livestock seeding (Jero, 2022). Cover crops are commonly seeded into the ground after cash crops have been harvested, though cover crops may be full season (i.e., planted independently of cash crops). Many who use a cover crop system take advantage of no-till seeding. Interseeded crops can be planted via arid broadcasting, conventional, or conservative planting practices. The problem with broadcasting is the lack of seed-to-soil contact, seeds getting caught in primary crop leaves, wind carrying seeds off, water flow bringing seeds to undesired locations, and not meeting seed depth requirements. However, it is a relatively quick and easy way to get the seed into the field. Another option is to drill the crop into the ground. A high-clearance drill will plant the seed in between the rows of the primary crop without causing damage to it. A significant challenge for cover crops is termination if cover crops are not used for grazing (full season) or precede a cash crop. Standard termination techniques include herbicides, winter kill, mowing, crimping, grazing, and burning. Cover crop termination happens prior to planting the cash crop. In contrast, interseeded crops are typically terminated by winter kill or chemicals, but herbicides are not a popular practice because of the drift that may kill off cash crops.

A study conducted by Palhano et al. (2018) used 11 different herbicides (alone or mixes) sprayed at 143 L ha^{-1} with a three-nozzle CO_2 pressurized backpack sprayer on cover crop plots to evaluate the effects of a pre-plant herbicide. Their findings concluded that 97-100% of cover crops consisting of cereal rye (*Secale cereale*) and wheat were controlled by glyphosate-containing herbicides, while glyphosate controlled less than 57% of legume cover crops. Hairy vetch (*Vicia villosa*), Austrian winter pea (*Pisum sativum subsp. arvense*), and crimson clover (*Trifolium incarnatum*) were best controlled with a mixture of glyphosate glufosinate, 2,4-D, and Dicamba, 81% (+) of legume crops was controlled by glufosinate. Further, 87% to 97% of legumes and 90-96% of cereal cover crops were controlled by Paraquat plus Metribuzin. Also noted was none of their treatments could effectively terminate rapeseed (Palhano et al., 2018).

Cover Crop Mixes Used in the Midwestern United States

Within the midwestern United States, cover crops are viewed as a regenerative row-crop farming practice, holding additional benefits for livestock grazing systems. However, the National Farmers Union estimated that only 12% of farmers utilize some sort of cover crops (O'Dell, 2020). Within the Midwest, the most common crops used for cover in SD, MI, and WI are annual ryegrass (*Lolium multiflorum*), radish (*Paphanus* *sativus*), and turnip (*Brassica rapa subsp. rapa*). Oats and sorghum/sudangrass (*Sorghum bicolor/Sorghum x drummondii*) are also in standard mixes for SD and MI. South Dakota and WI commonly share Dwarf Essex Rapeseed (*Brassica napus Dwarf Essex*), while Michigan and WI have triticale (*xTriticosecale*) added to their mixes (Table 1).

Annual ryegrass produces a high amount of biomass and quickly establishes. Annual ryegrass as a cover crop reduces compaction, captures NO^{-3} from the soil, and prevents erosion. Triticale is a cross of wheat and rye, and although it may not create a lot of biomass, it does not tie up as much N in the spring. It is typically planted in early fall and is terminated with grazing, mowing, crimping, tilling, and chemical herbicide applications. Sudangrass/sorghum-sudangrass is known to produce abundant biomass, increase OM, and reduce compacted soils and nematode populations (Rooney et al., 2007). It is typically planted in mid-July and terminated with frost kill. The deep taproot structure of forage radishes and turnips helps to reduce soil compaction, suppress weeds, and capture nitrogen in the soil to prevent leaching, typically planted early in spring, early summer, and even in early fall.

Considering corn production in WI, winter wheat and winter rye are the most common crops interseeded because winter wheat gives a producer a multi-cash crop, and rye is easy to establish. Other interseeded crops in WI include oats, medium red clover (*Trifolium pratense*), crimson clover, daikon radish (*Raphanus sativus var. Longipinnatus*), dwarf Essex rape, seven top turnip, and annual ryegrass.

South Dakota cover crops following corn harvest for dry grain are hard to establish because of the short growing season. Some producers try to plant a winter annual like cereal rye, wheat, or triticale solely for ground cover. Interseeding is becoming more popular, and producers in SD tend to plant small, seeded crops. Planting dates for cover crops in SD are May 1- August 5 for warm-season plants with winter kill, early spring – August 20 for cool season winter kill, and August 1 through winter for species that do not winter kill.

In SD, Tobin et al. (2020) conducted a study demonstrating the impacts of grazing and cover crops on soil health. They had four treatments 1) grass blend [oats, sorghum, pea, cowpea, lentil (*Lens culinaris*), and radish] 2) legume blend (pea, oats, lentil, radish, cowpea, and sorghum-sudangrass) and 3) equal blend (oats, pea, sorghum, lentil, cowpea, and radish) and 4) a control (fallow). Each crop was followed by rye and a three-year corn, soybean, and rye rotation and was grazed by beef cattle. Tobin et al. (2020) found that the mean SOC (g/kg) was significantly higher in the grass blends (23.49) for post-grazed at 0-5 cm soil samples when compared to the legume blend (21.74), equal blend (21.59) and control (20.24), which were not significantly different from each other ($P > 0.05$). However, they did find a negative impact with grazing for SOC, soil bulk density, and soil water retention when comparing grazed vs. ungrazed plots (Tobin et al., 2020).

Malone et al. (2022) researched the feasibility and yield effects on cover crops in WI. They used five different cropping systems from 2017 to 2020 with rye or oats (broadcasted or drilled) following corn or soybeans and berseem clover (*Trifolium alexandrinum*), red clover or oats and rye (frost seeded or drilled) following winter wheat. They found that drill seeding cover crops after corn and soybean harvest was not optimal for WI. In contrast, with preharvest seeding, they found that it gave the greatest soil coverage, with the most significant benefit being erosion control. Frost seeding red clover into winter wheat was the most successful treatment. Corn yields decreased by

5.8-8.6% due to being more sensitive to the cover crops when compared to soybean and winter wheat (Malone et al., 2022).

Frisk et al. (2001) used annual legume cover crops to suppress weeds in a no-till corn rotation in MI. The cover crops they utilized were two annual medic species, Santiago burr medic (*Medicago polymorpha*) and Mogul barrel medic (*Medicago truncatula*), Bigbee berseem clover (*Trifolium alexandrinum L.)*, and medium red clover (*Trifolium medium*) compared with a control of no cover crop. The cover crops were drilled into a no-till wheat field, and were terminated with winter kill, except for red clover, which was destroyed with herbicide. Following the termination of cover crops, corn was planted. They found that the annual medics and red clover did occasionally reduce weeds when planted before no-till corn ($P \leqq 0.05$) (Fisk et al., 2001). While each study was conducted in different states, with different climates and crops, they all demonstrated at least one or two of the five principles of regenerative agriculture. Cover crops' role in achieving regenerative farming systems is growing, especially in the United States dairy industry, which is heavily regulated for environmental sustainability.

Given the growing demand for regenerative cropping systems to inset and offset C and mitigate adverse environmental externalities, the United States dairy industry is particularly interested in cover crops. For example, MI has many dairy farms, creating a precedent for adapting the use of cover crops into these operations. The most common unharvested cover crops are rye, oats, red clover (*Trifolium pratense*), and radish. Some Michigan producers also utilize typical cover crop plants, such as oats/field peas or triticale/field peas, forage sorghum, sudangrass, or a sorghum-sudangrass to fill gaps during cash crop seasons to be grown as feed to be ensiled or fed to their dry cows/heifers

(Cassida, personal communication, September 2021). However, interseeding is a rare practice for MI producers as alfalfa and crops such as timothy grass, tall fescue, and meadow fescue will be planted by themselves for a few years as part of their crop rotations to improve yield, persistence, and increase nutrition. Oats may be used as a nurse crop but then harvested or ensiled for cattle feed (Cassida, personal communication, September 2021). In MI's upper peninsula, planting dates for cool season grasses and legumes are May 1-June 1 or July 10-August 1, and warm-season grasses and legumes are May 15-June 30. In the north half of the lower peninsula, cool season grasses and legume planting dates are April 20-June 1 or July 15-August 1; for warm-season grasses and legumes, it's May 15- June 20. Lastly, in the south half of the lower peninsula, cool season grasses and legumes planting dates are April 10-May 20 or July 20-August 15, and warm season grasses and legumes planting dates are May 5-June 30 (MCCC-MSE, 2019).

Wisconsin dairy producers, that utilize the tool of cover crops, plant after corn silage harvest in September/October to keep their soil covered and reduce nutrient loss. They apply manure produced in the fall and use these cover crops as a spring forage source. The most popular plants producers use for this are rye and triticale separately. Oats are a popular option for summer-seeded covers and are planted in August. Many popular WI cover crops are planted in the late summer/fall around harvest and before spring planting.

Dairy Systems Within the Midwestern United States

A significant component of Midwestern agronomic production is dairy operations. Within the United States, there has been a shift in dairy production which includes the number of producers decreasing and the size of operations increasing. In the Midwest, there has been a decrease in the number of dairy operations due to financial challenges (USDA, 2020). States that have been noted for this shift are WI and MN—in 2018, WI, MI, and SD produced ~14, ~5, and ~1 million kg of milk, respectively (USDA, 2020).

Holding cows in large barns/lots has become a widespread practice to manage growing dairy cow herd numbers effectively. Consequently, grazing has become less common, resulting in producers having to produce or purchase feed to provide for their cows in concentrated animal feeding operations (CAFO; USDA- NRCS, 2021). The CAFO dairy production system has led to significant concerns about environment, welfare, and profits. Further, milk prices have been fluctuating, which causes risk for producers' income though costs, like feed, remain constant (USDA, 2020). Not only are there financial concerns with dairy production, but there are environmental concerns. Dairy farms have been linked to negative impacts on water and air quality. Water concerns are runoff, sediment erosion, and NO^{-3} leaching from urine. Air quality concerns have arisen from greenhouse gas emissions (GHG) and ammonia emissions from manure (Rotz et al., 2009). Producers can utilize regenerative agricultural practices (such as cover crops) to counteract some of the negative outputs from dairy operations.

Soil Carbon Overview

A major goal for regenerative agriculture is C mitigation and sequestration. Carbon in the environment is vital because, in combination with N, it makes up 95% of the biosphere, and C composes part of plant tissue (Nieder and Benbi, 2008). Plants absorb atmospheric C through photosynthesis and then use it to complete the photosynthetic process. In turn, plant residue and roots decompose, creating SOM, a fraction of which is C (~58%) (Neitsch et al., 2011) that is either sequestered or released into the atmosphere as CO_2 (Nieder and Benbi, 2008). Total soil carbon (TSC) is defined by Nieder and Benbi (2008) as the sum of SOC and soil inorganic carbon (SIC). Soil inorganic C is living and dead OM (Nieder and Benbi, 2008). Models can help aid producers in management decisions with science-based predictions to recognize practices that will improve their soil C sequestration by effectively reducing the quantity that is released into the atmosphere.

A seminal paper published in 1938 by Callendar proposed the warming mechanism associated with increased global temperatures caused by greater concentrations of CO_2 enhancing the global greenhouse effect (Callendar, 1938). Norman Phillips, a major proponent of climate models, published his first general circulation model in 1956. His 2-layer, hemispheric, quasi-geostrophic computer model estimated weather and modeled Earth's climate (Phillips, 1956). This model led to the age of computer modeling in climate, which escalated to the Intergovernmental Panel on Climate Change (IPCC). In 1990 the Intergovernmental Panel on Climate Change published its first report; in 2013, it published its fifth (Stocker et al., 2014). These efforts were significant because of two key issues relating to global climate change over the past century. The first was ozone layer depletion in the 1970s, which caused considerable environmental concern. Molina and Rowland (1974) published a paper about chlorofluorocarbons (CFC) that were destroying the atmospheric ozone, which was followed by a study regarding a hole in the ozone layer above the Antarctic (Farman et al., 1985).

Conversely, current sustainability efforts are chiefly concerned with trapping GHG, causing an extensive gas buildup. Researchers as early as the 1980s have expressed concern for the gases trapped in our ozone layer. A climate paper reported that trace gases of CH_4, nitrous oxide, and CFC are less present in our atmosphere than CO_2 (Lashof and Ahuja, 1990). The problem with the more limited trace gases is that they absorb infrared radiation at a higher strength than CO_2. These trace gases have been attributed to the 43% increase in global radiative force from 1980-1990 (Lashof and Ahuja, 1990). Thus, the continued accumulation of GHG has raised worldwide concern, and industries like agriculture have become subject to significant political and societal pressure for products that reduce GHG emissions and improve C sequestration.

Carbon Models Overview

Identifying strategies for GHG mitigation and C sequestration on agricultural lands is problematic because it takes a long time to detect the change and to account for actual mitigation and sequestration quantities due to the inherent fluxes. Modeling C is important because it can show us the potential future and teach us valuable lessons on managing C in soils and atmosphere. Further, since we cannot measure every C flux, mathematical simulation modeling, including life cycle assessment, are the only methods to get a quantified estimate of these processes (Dillon et al., 2021).

One resource stakeholders can use to assess C fluxes is Climate Interactive: The C-ROADS Climate Policy Model (Sterman et al., 2012). The C-ROADS model includes an agriculture policy simulator to learn more about building a sustainable food system, including a soil C and biomass sub-model to look at deforestation, afforestation, and change in soil C. The C-ROADS model also has the capability to investigate tillage practices of farming and soil conditions. They have found three basic principles; that sequestration takes time, has limits, and the results will hold for any negative emission (Sterman et al., 2012). Currently, the C-ROADS model is used all over the world to address issues with climate dynamics. This provides a tool to explore different policy solutions that have the potential to decrease GHG. However, according to the Climate Interactive documentation, soil and C dynamics within agronomic systems are calculated on a large level of aggregation, and opportunities exist for implementing more granular C dynamics (e.g., on-farm or watershed level). New or enhanced models need to be developed for more precise estimates to evaluate management decisions of soil C more adequately on agricultural lands (crop and livestock; Sterman et al., 2012).

Agriculture Carbon Models Overview

Many field-level agriculture models exist that include soil C estimation, such as the Soil and Water Assessment Tool (SWAT), Denitrification-Decomposition model (DNDC), Agricultural Production System sIMulator (APSIM), Agriculture Policy Extender Model (APEX), and the Environmental Policy Integrated Climate model (EPIC) (Jiang et al., 2017), which differ in trade-offs and capabilities. The SWAT, developed by Dr. Jeff Arnold, is a hydrological model that evaluates the response to non-point source pollution with land use change that provides a reference for land pattern optimization for watersheds (Shen et al., 2008). Although a good tool, the SWAT model only allows for one river outlet in the watershed (Shen et al., 2008), limiting the analysis. The DNDC model simulates the most GHG fluxes compared to other models, and it also accounts for compaction effects on bulk density (Brilli et al., 2017). It can also simulate harvesting, mowing, fertilization, tillage, and irrigation. Results are limited by the simulation of fast drainage, affecting water losses in excess of field capacity and will negatively influence denitrification estimates in wet soil. Another limitation is that it does not simulate heterogeneous soil profiles (Brilli et al., 2017). The APSIM model simulates the interactions with plants, animals, soil, climate, and management in agricultural systems. This approach allows for evaluating the whole-farm system, including crop sequences and pasture rotations with livestock (Brilli et al., 2017). Although, some estimations are deficient in soil C due to the inadequacies of modeled manure and tillage processes (Causarano et al., 2008). An advantage of the EPIC model is that it can simulate compaction effects on bulk density, harvesting, mowing, fertilization, tillage, and irrigation (Brilli et al., 2017). The Integrated Farm System Model (ISFM) is another model that simulates crop production, feed use, and manure nutrients being returned to the land. The ISFM model also affects crop growth on a daily timestep basis (a discrete event-driven model) that uses soil water, N availability, ambient temperature, and solar radiation.

The ISFM model investigates crop growth and includes predicting animal response to the nutrient value of available feeds and feed allocation. With all these components, the ISFM model can analyze nutrient flows that predict the accumulated nutrients in the soil and those that are lost to the environment. One of the main differences between IFSM is that it operates on all significant farm components. Since it is a processed-based model, it can integrate the elements that represent the interactions (biological and physical) that happen on a farm. Another whole farm model is the HOLOS model, and this empirical model is used to simulate different farm practices that can reduce GHG emissions; created by Agriculture and Agri-Food Canada (Little et al., 2017). Management practices that can be adjusted in this software program include feed for livestock, tillage reduction, or incorporating perennial forages (GC, 2022). Another C model is the CENTURY model, which has a four-pool SOM sub-model that models C, N, P, and sulfur (S). The accumulation or loss of each pool is based on SOM turnover rate and decomposition characteristics at a 20 cm soil depth. This model utilizes different plant-soil ecosystems to represent C and nutrient changes in a particular system (Kelly et al., 1997).

The CENTURY model eventually led to the development of the DAYCENT model. DAYCENT is a terrestrial ecosystem model that simulates C, N, and trace gas exchanges among the atmosphere, soils, and vegetation (Del Grosso et al., 2001; Parton et al., 1987). The previous authors reported the difference between the two models is that the CENTURY model has a monthly timestep, while DAYCENT has a daily timestep. The DAYCENT model estimates the trade-off of C, N, P, and S with the plants, soil, climate, and atmosphere. Additionally, Del Grosso et al., (2001) stated that the DAYCENT model simulates natural/management events, such as fire, cultivation, and grazing, while accounting for plant growth. The DAYCENT model can more precisely simulate plant residue and root decomposition, and flows of nutrients, soil water, and soil temperature (Del Grosso et al., 2001).

For example, the DAYCENT model was used to run a 100-year simulation of different land management practices in the United States Great Plains that affected soil C, N, nitrous oxide (N_2O), C storage, NO^{-3} leaching, and crop yields (Del Grosso et al., 2001). They found that N gas fluxes were represented fairly in the model when comparing the observed and simulated emissions data for monthly N_2O ($R^2 = 0.29$) and nitrogen oxides (NO_x) ($R^2 = 0.43$). Further, the DAYCENT model simulations indicated that crop fallow rotations and conventional tillage reduced SOM significantly (Del Grosso et al., 2001). Similarly, a study used the DNDC to forecast SOC levels until 2050 (Bierer et al., 2021). They used variations of manure management, tillage practices, winter cover crop, and crop rotation. The SOC was simulated well using the default DNDC model, although the default and calibrated DNDC models had a sizeable absolute error when different manure applications were simulated. This study by Bierer et al., (2012) reported that the rotation of wheat-potato-barley-sugar beet did not significantly change in 8 years without the effects of manure ($P = 0.905$).

Another well-used model is the COMET model, the primary model for C sequestration for the USDA-NRCS (Paustian et al., 2018). The COMET model is based on DAYCENT and is used to quantify GHG and C sequestration in a web-based tool for producers. This model allows for assessing CO_2, methane (CH_4), and N_2O for CO_2 removal into biomass and soil sinks. It uses the USDA GHG inventory guidelines with a spatial user interface at field and subfield scales. This includes taking a snapshot of current management practices and projects into the future for GHG balance for an entire farm operation for subsequent years. It also allows the user to assess up to eight scenarios simultaneously (Paustian et al., 2018). The growing demand for sustainable dairy production systems that inset/offset the C footprint, increase production, and reduce costs/lead to increase marketability (e.g., market premiums) has accelerated the role and demand for modeling C on single farms and supply sheds.

The Role of Models for Dairy

Managing a dairy operation is highly complex because of the interconnections between animals, manure, soil, and stored crops with their performance standards. Dairy producers must meet animal growth and performance requirements while managing manure storage capacity and quality (chemical composition), soil, and crops for growth and environment, while also maintaining correct crop storage quality and availability/time (Kebreab et al., 2019). Environmental factors and government regulations heavily influence dairy farms, which further increases the difficulty of performing these standard farming processes. Fortunately, regenerative or sustainable production methods have been shown to decrease environmental impacts while maintaining or improving production.

Additionally, consumer demand has provided motivation and new markets for regenerative or sustainably produced dairy products. Although regenerative practices can improve an operation, it is impossible to do all practices at once and realize production or financial success. Thus, models can help evaluate different regenerative management practices and then identify the best regenerative strategies that align with farmer goals while avoiding detrimental or ineffective ones. Overall, the best methods maintain or improve production while improving aspects like soil health (i.e., high-leverage decisions that avoid unintended negative consequences). Even though the applications for quantifying soil C changes in agronomic dairy production are important, there are further environmental GHG considerations for beef production efficiency and sustainability.

Overview of Global and United States Beef Cattle Emissions

According to the Food and Agriculture Organization of the United Nations (FAO), "naturally occurring methane (CH_4) is generated by anaerobic fermentation where bacteria break down OM producing hydrogen (H_2), carbon dioxide (CO_2) and CH_4" (FAO, 2022). Ruminant animals naturally generate CH_4 within the rumen from microbes breaking down feedstuffs. Enteric fermentation is part of a ruminant digestive process. Methane production is related to how much feed a ruminant animal consumes, the quality and type of feedstuff, the size and growth of the ruminant, and individual animal efficiency. Ruminants release CH_4 into the air mainly by eructating. An estimated 2-12% of energy intake is lost through enteric emissions (Johnson et al., 1993; Blaxter and Clapperton, 1965). One misconception about cattle producing methane is that it comes from flatulence; however, 90-95% of gases released from cattle come from eructating (Johnson et al., 1993). Methane is one of the leading GHG gases; others are water vapor (H_2O), CO_2, and N_2O. These gases trap heat in the Earth's troposphere, increasing global warming. According to the United States Environmental Protection Agency (EPA), in 2010, the sectors of Agriculture, Forestry, and other land use comprised 24% of the global GHG emissions (EPA, 2023). Electricity and heating were another large contributor (25%), followed by industry (21%), transportation (14%), other energy (10%), and buildings (6%). Out of the 24% from agriculture and forestry, cultivation and livestock make up the majority of GHG emissions; 20% of the 24% is offset when accounting for the CO_2 that is taken out of the atmosphere by sequestering C with sustainable agriculture operations that trap CO_2 in plants, trees, and soil (EPA, 2023). Within the United States, agriculture only makes up 10% of the GHG emissions reported in 2018 (EPA, 2023), while transportation (28%), electricity (27%), industry (22%), and commercial and residential (12%) all surpass agriculture. Of the 10% GHG attributed to agriculture, only 28% is from enteric fermentation of ruminant animals (beef and dairy cattle), which includes only 2.8% of total enteric emissions, and of 2.8%, only 1.8% is CH_4 (EPA, 2023). Further, CH_4 in the atmosphere has a lifespan of 9 years, while CO_2 has a lifespan of 100 years (Jacob et al., 2016).

Reducing CH_4 globally can increase air quality and decrease global warming potentials. Although this cannot happen on a small scale, it must occur worldwide because of how CH_4 mixes in the atmosphere (Jacob 2019). A wide range of environmental sources can produce CH_4, besides livestock, including wetlands, coal mines, fire, oil/gas, and waste (EPA, 2023). Most of the public believes that GHGs are causing climate change, targeting CH_4 as the leading cause. According to the Environmental Defense Fund, CH_4 is 80 times more powerful in terms of warming power than $CO_{2.}$ While CO_2 has a longer-lasting effect in the atmosphere (EDF, 2023). Consequently, CH_4 from the agricultural sector, specifically ruminants like beef and dairy cattle, has come under extreme pressure for mitigating GHG emissions, while maintaining agriculture product(s) quality and increasing productivity and efficiency (kg milk/meat per kg feed intake; CO_2 eq/kg product).

Aside from dairy cattle, the impact of the beef livestock sector is vital regarding meat products and sustainability, and understanding the role of grazing livestock operations on intact rangeland systems is paramount (Bai and Cotrufo, 2022). In the United States, roughly 213 million ha are privately owned range and pastureland, equal to 27% of the total acres in the lower 48 states (NRCS, 2022). Rangelands in the United States comprise ~30% of the land cover, equating to 312 million ha. Within the United States, the Northern Great Plains (NGP) contains one of the few remaining intact rangeland ecosystems that produce beef cattle. These rangelands are mixed-grass prairie

–vegetation is a mix of tallgrass, midgrass, and short grasses. In native rangelands, an example of a tallgrass is big bluestem (*Andropogon geradii*), a midgrass example is western wheatgrass (*Agropyron smithii*). An example of an exotic midgrass is Kentucky bluegrass (*Poa pratensis*). Native short grasses are blue grama (*Bouteloua gracilis)* and buffalo grass (*Buchloe datyloides*) (Gartner and Sieg, 1996). Rangelands are extensive systems producers can utilize for livestock growth and production (Menendez et al., 2020). Although rangelands are a great source of forage for cattle and wildlife, forage production is limited by rainfall, temperature, and stocking rates. Forage production depends on the area and type of rangeland available.

South Dakota is a critical beef cattle producing state within the NGP. In SD alone (as of December 2017), there were ~4 million cattle and calves, which sustain roughly 20% of employment. Beef production is a significant source of revenue for the state bringing in $25.6 billion annually (USDA, 2017). From 2012 to 2017, the number of farms that produced beef cattle, according to the 2017 USDA Census, decreased by 714 farms. However, beef cattle numbers increased by 189,242 head during this period. This suggests that beef cattle efficiency has increased on rangelands.

Types of Grazing Systems

Grazing animals can be managed in many ways on rangeland. One grazing method is continuous or season-long grazing, where animals stay in an area (pasture) all year, and the rangeland is not rested (Howery et al., 2016). Season-long grazing is one method that can lead to overgrazing. Overgrazing is when a plant is bitten several times during the growing season, causing plant regrowth or root storage limitations (Savory, 1988). This damage can be offset by recycling plant nutrients in animal waste products such as manure and urine (Hodgson, 1990). Another grazing type is intermediate grazing, when livestock are moved in and out of an area, being set to graze the forage quickly and then moved into a new location before plant damage occurs (Hodgson, 1990). This method is also known as rotational grazing. Another grazing type that is important for cow-calf operations is creep grazing. Creep grazing is a management tool that allows livestock's offspring to graze a particular area where their mothers cannot. Creep grazing can be set up with any grazing rotation, but additional fencing infrastructure is required to allow calves to pass through into another pasture area while retaining cows (Hodgson, 1990).

Deferred rotation is a method that gives rest to one pasture during the growing season (Howery et al., 2016). According to Herring (2014), deferred grazing utilizes 50% or more of the land while the other has time to rest. For example, the Merrill Four-Pasture Deferred System is commonly used. This system uses four pastures as new areas to rotate animals into, at four monthly intervals. Three of the four pastures are grazed with the appropriate number of animals in each pasture. With this system, it only takes four years for each pasture to be rested once each season (Herring, 2014). Short-duration grazing is the most labor-intensive system. Like intermediate grazing, a small area is intensively grazed to limit animal selectivity and increase rest time on the other pastures (Herring, 2014). Finally, rest-rotation is a system initially designed to rest a pasture for a whole year, unlike deferred, that only rests the rangeland during the growing season (Howery et al., 2016). Management intensive grazing (MIG), adaptive multi-paddock (AMP), and precision grazing are more advanced types of grazing that implement the same grazing principles of animal nutrient demands, plant regrowth, and environmental health to maximize each component, but significantly increase labor, management, and infrastructure requirements. Precision grazing seeks to turn physical work into a cognitive endeavor with technology. It achieves AMP and MIG with precision management tools (i.e., virtual fencing) to make physical management decisions (Menendez et al., 2022). Successfully implementing a grazing plan is essential for the viability of ranching operations, especially in areas where grassland conversion and environmental sustainability concerns affect regional economic viability (Tedeschi et al., 2019; Menendez et al., 2022).

Considering Dry Matter Intake of Grazing Animals

An essential factor for any grazing system is dry matter intake (DMI). Dry matter intake is the total daily consumption of feed on a moisture-free basis (USDA, 2020) compared to as-fed, which is the actual weight of feed consumed with moisture (USDA, 2020). Dry matter intake is crucial because it helps estimate the animal's nutrient intake, allows for the comparison of different feedstuffs, and helps accurately reach the feed requirement goals of the animal (USDA, 2020).

Van Soest (1994) states that animal age is one factor that affects feed intake. Yearling animals will consume more feed per unit of body weight (BW) when compared to calves. Not only does age affect feed intake, but so does the animal's physiological state. Feed intake can increase by 35-50% for lactating animals compared to non-lactating animals. There can be an increase of 30% DMI for forages alone for lactating animals (Minson and McDonald, 1987). It has been reported that forage intake for grazing animals was maximized when the forage availability was 2,250 kg DM/ha and decreased by 60% when the allowance was 450 kg DM/ ha (Rayburn, 1986). Thus, animals have different requirements for class and stage of production, and this is relative to changing plant nutrients throughout the year (Rayburn, 1986). Young plants are low in structural carbohydrates, highly nutritious [high crude protein (CP)], and digestible for the ruminant animal. As the plant begins to mature, it increases in structural carbohydrates (high fiber). Once the plant is in the reproductive stage, it produces a seed head, and most nutrients are in the seed. The stem and leaves are high in fiber and are less nutritious (lower CP) and digestible. Perennial plants become dormant in conditions where growth cannot occur (winter/drought), and the plant has decreased protein, digestible energy, and palatability (Herring, 2014).

Intake for the grazing animal is limited by stocking rate, and plant density and morphological stage (Colucci et al., 1982). Hodgson (1990) defines the stocking rate as the number of animals in an area for a given time period. Carrying capacity is another consideration for grazing animals, and this is the ideal number of animals in an area that can be fed (i.e., grass availability) without causing long-term ecological damage (Herring, 2014). It has also been shown that cattle graze more frequently when the days are longer, with a 1.5-2% decrease within months with shorter photoperiods (NRC, 1996). Areas with colder temperatures can decrease animal intake by up to 47% (Adams et al., 1987), and limited rainfall can reduce it by 10-30% (Galyean and Gunter, 2016). Additionally, the energy requirement of the animal determines DMI. A large portion of the animal's total energy (70-75%) goes to maintenance, and then what is left over goes to growth, reproduction, and milk production (Ferrell and Jenkins, 1985).

Overview of Field Research to Estimate or Predict Dry Matter Intake

Methods such as direct observation, depletion of food, hand-plucking, total fecal output, and internal/external markers are used to estimate the intake of forages by grazing cattle (Smith et al., 2021). A review by Bjugstad et al. (1970) stated that direct observations of domestic livestock could help ascertain what they eat, when they eat different species, where they are eating, and how the animal eats on rangelands, but cannot establish how much they are consuming, and therefore is a poor indicator of DMI (Bjugstad et al., 1970). One of the most effortless techniques for estimating grazing is the depletion of a food resource (Mayes and Dove, 2000), which bases intake estimations on how much herbage mass is left post-grazing. Since plants naturally grow and are defoliated, these techniques are only suitable for a short time scale, and at longer time scales, consumption would be underestimated.

The hand-plucking method is used for forage intake estimations, diet selection, and diet quality. Hand-plucking uses a technician that watches grazing animals and picks "bite-sized" grass swards to mimic the animal while it is grazing. To successfully do this measurement, it needs to be done in a low-stocked pasture, so it is guaranteed that there will be similar plants to pluck next to where the animals are grazing (Cook, 1963). One limitation is that it has been deemed unsatisfactory for mixed species pastures (Cook and Harris, 1951). However, it has been stated that a skilled observer could mimic bite size and grass swards with homogeneity in a pasture of a few grass species (Bonnet et al., 2011).

Total fecal output has been used with fecal markers, such as chromium (III) oxide (Cr_2O_3), to estimate intake on the day the marker was administered. Researchers then collect feces a few times a day and measure the amount of the marker in the feces. Smith et al. (2021) used the procedure previously stated above and found a significant variation in the fecal collection from cows, most likely due to uneven grazing distribution throughout the day compared to steers. Another issue with this method is if Cr_2O_3 gelatin capsules are fed by being mixed in with a concentrate feed, there is no guarantee the animal will get the correct dose.

Another method to measure DMI is internal and external markers which overcome the limitations from the total grab and pull technique and total fecal collection. Differences exist between internal and external markers and the materials of which they are composed. Velásquez et al. (2021) used 12 bulls split into groups and fed four different diets ad libitum for 38 days. The results indicated that Cr_2O_3 + indigestible neutral detergent fiber and Cr_2O_3+ indigestible acid detergent fiber was more precise at estimating dry matter demand (DMD), fecal output, and DMI when compared to total-tract apparent digestibility, actual fecal production, and real DMI (equation 1) (Velásquez et al., 2021).

$$(1)\ \mathrm{RDMI(g/d)} = \text{ daily feed offered } (\mathrm{g\,DM/d}) - \text{ orts collected } (\mathrm{g\ DM/\ d}).$$

Total voluntary intake from the fecal output (FO) and DMD were estimated using the following equation (2):

$$(2)\ \text{DMI estimated by markers } \left(\frac{\mathrm{g}}{\mathrm{d}}\right) = \ \mathrm{FO}\frac{\left(\mathrm{kg}\,\frac{\mathrm{DM}}{\mathrm{d}}\right)}{1} - \text{diet DMD}$$

It was found that none of the markers used [internal: acetyl bromide lignin cutin, indigestible neutral detergent fiber, and indigestible acid detergent fiber; external: Cr_2O_3 and titanium dioxide (TiO_2)] for sampling pairs resulted in accurate DMI estimates for all diets (Coleman, 2005). A major limitation in this study and others is that marker recovery may be poor. Therefore Coleman (2005) stated, a total fecal collection from at least one animal is important to make accurate adjustments. Although it has become the most popular method over the past 60 years, there are many concerns with measurement errors for fecal output and digestibility of the whole diet. Fecal markers must be assumed to be recovered, proportionately and evenly excreted, and to not interfere with normal rumen activity (Coleman, 2005).

Using an esophageal fistula allows forage sample collection from the animal (Coleman, 2005). This enables scientists to collect forages before they drop into the rumen to identify what and how much they are consuming. Although this practice has been used for many years, there are some issues with the calculations, such as saliva contamination and the small amounts of forage that slip past the fistula and into the rumen. Also, the same problems can occur with rumen-fistulated cattle, but cattle have been observed to experience less stress with this method (Coleman, 2005).

Although these methods are available, they are limited in their ability to account for different environmental factors, management practices, and animal physiological changes (Undi et al., 2008). It is also impossible to weigh feed refusals in a grazing setting (Coleman, 2005). Field-based studies have laid the groundwork for estimating DMI but are tedious and time-consuming. With the help of equations and models, researchers can better predict DMI reducing cost and time constraints.

Overview of Grazing Models to Estimate Dry Matter Intake

With the help of models, we can account for different factors that we cannot directly measure. The National Academies of Science, Engineering, and Medicine (NASEM) models account for heat loss/gain, milk production, grazing forage allowance, breed, physiological state, and activity (NASEM, 2016). While the NASEM model can provide a basis for the intake of grazing animals, many of these equations were initially calculated for animals with little movement (Coleman et al., 2014).

Bandyk and Cochran (1998) collected 20 years of past intake observations and compiled a database to address and resolve the limits of pre-existing DMI models. While conducting their research, they found that 80% of the 42 papers published at that time had a sample of steers (growing cattle), with a forage (CP; %) in the range of 1.9-27.8%, and neutral detergent fiber of 42-82%. In a single-variable regression model, they identified five forage variables that could explain approximately half the variation within the data set in intake per unit of BW. They found that forage acid detergent fiber (ADF) and CP were the best predictors. Still, separately they could only account for ~30% of the variation for intake (Bandyk and Cochran, 1998).

One method to calculate DMI is to use the average BW of the animal based on class. The USDA (2020) reported that for this method, a producer needs to 1) use the average weight of the animal within its class. For beef cows, depending on the breed, size, energy loss, and stage of production, each animal will consume 1-3% of their BW shown in equation 3:

$$(3)\ \mathrm{DMI\ (kg)} = \mathrm{BW\ (kg)} * (\mathrm{DMI\%\ BW} / 100\ \mathrm{(kg)})$$

Where BW (kg) is the estimated average body weight of the cow, DMI%BW is the 1-3% estimated percent of BW that represents DMI.

Undi et al. (2008) predicted forage DMI using the forage net energy equation. This equation used animal body weight and standing forage NE_m. The equation (NASEM, 2016; NRC 1996) is:

$$(4)\ \mathrm{DMI}(\mathrm{kg\ d^{-1}}) = \mathrm{SBW}^{0.75} * (0.1493 * \mathrm{NE_m} - 0.046 * \mathrm{NE_{m^2}} - 0.0196)$$

Where, $SBW^{0.75}$ is the shrunk metabolic body weight (kg), and NE_m is standing forage net energy for maintenance (Mcal/kg DM). The NE_m was calculated as:

$$(5)\ NE_m = (2.018 - 0.038 * ADF) * 0.7$$

Where ADF is the acid-detergent fiber content of the standing forage (%; Van Soest, 1994).

The ADF was obtained by hand plucking representative samples and using an ANKOM 200 fiber analyzer. This study used British-continental cross beef steers that grazed three 28-day periods from late May/early June, with an estimated 1000 kg/DM/ha, until August. They also used other DMI estimation techniques, but of all of them, the net energy equation was the least variable. Overall, empirical equations are a tool that may give DMI estimation reliability under similar environmental conditions (Tedeschi et al., 2019). Cattle on rangeland are often a variety of classes and physiological stages, making management difficult. Balancing these factors with seasonal changes in CP and precipitation is vital for determining forage DMI, ultimately impacting stocking rates (animal units per ha per month).

Grazing Cattle on Rangelands

Knowledge of cattle intake in rangelands is essential to determine the nutrients that livestock require and evaluate feed efficiency (Fox et al., 1988). Feed efficiency is used to quantify milk and meat production from feed consumption (Korver, 1988). According to Dickerson (1978), 5% of all dietary energy used for beef production goes toward protein deposition. When compared to other livestock, cattle are inefficient animals. Thus, it is crucial to evaluate feed efficiency for producers to extend pasture availability, reduce supplement costs, and guide genetic selection within their herd (Hill, 2012; Dickinson et al., 2013). Feed efficiency cannot be directly estimated for grazing animals because their actual DMI is unknown. Smart et al. (2010) conducted a study across the United States on harvest efficiency for grazing animals in light, moderate, and heavy stocked pastures. Harvest efficiency is the forage ingested by the grazing animal from the forage produced and is reported as a percentage (Butler et al., 2003). Smart et al. (2010) used three different intake equations for harvest efficiency. For each equation, they found significant differences in the stocking rates ($P = 0.0001$), with the goal of 25% harvest efficiency, the moderately stocked pastures were closest, while heavily stocked were 13-16% higher, and lightly stocked pastures were 6-10% lower (Smart et al., 2010). These findings support the continued need for estimating DMI as precisely as possible through modeling, especially as ranchers experience more significant perturbations in forage production and consumer concerns (Menendez et al., 2022). A major consideration of grazing management is how forage and DMI factors, and DMI estimation methods, can be further refined to meet production goals and decrease GHG production from rumen fermentation.

How Methane is Produced in the Rumen

Ruminant animals are one class of animals that can turn grass into meat. This is accomplished through fermentation with bacteria in the rumen. Since cattle cannot digest the fiber they consume, they utilize microbial bacteria, fungi, and protozoa (10^{10} – 10^{11}cells/ml) that produce enzymes capable of breaking down fiber and polysaccharides (Matthews et al., 2019; Terry et al., 2019). Microbial fermentation then, in turn, produces volatile fatty acids (VFA) that are used by the ruminant animal (Terry et al. 2019). The

VFAs (propionate, acetate, butyrate) are absorbed across the rumen wall and supply a significant component of the animal's energy.

Unfortunately, this fiber digestion process results in CH_4 production while microbes feed on short-chain fatty acids, amino acids, hydrogen (H_2), and CO_2 (Zhou et al., 2009). The process of CH_4 production is known as methanogenesis where the rumen uses H_2 and CO_2 to lower the hydrogen pressure, thus generating CH_4. The production of CH_4 can cause up to 6% energy loss and plays a part in contributing to global GHG emissions (Zhou et al., 2009; Johnson and Johnson, 1995). The process of releasing enteric emissions (CH_4) through eructation happens from fermentation in the rumen, which causes ruminant animals to belch gases releasing the buildup in the rumen (Thorpe, 2009); 98% of the CH_4 produced by the rumen is released by the nose and mouth of the ruminant animal (Thorpe, 2009).

Methane produced by the rumen is directly correlated to forage quality (NASEM, 2016). Methane emissions are shown to decrease when DMI decreases, the concentrate to roughage ratio decreases, fibrous concentrate is replaced by starchy concentrate, corn replaces barley, silage replaces hay, and forage particle size is decreased (NASEM, 2016). This, in turn, alters the proportions of VFA production. Acetate and butyrate are associated with higher methanogenesis. A meta-analysis used dairy cows to examine the repeatability and between-animal variation of digestion and fermentation related to CH_4 yield (Cabezas-Garcia et al., 2017). The average concentrate to roughage ratio for the dairy cows' diets was 41:59 (DM basis). The concentrates consisted mainly of cereal grains, by-products from the food industry, and protein supplements (canola and soybean meal). Silages were the primary sources of forage, corn silage being the most used and with a few that had either legume silage or whole-crop silage. It was determined that rumen fermentation could be closely related to CH_4 production, which aligns with previous literature (Tedeschi and Fox, 2016). Further, it has been reported that high acetate and butyrate production increased CH_4 production while propionate reduced CH_4 production in the rumen (Zhou et al., 2009). Thus, measuring or quantifying GHG from cattle eructation is essential to understand the true impact of the efficiency of beef cattle and its subsequent effects on the environment.

Precision Measurement Technology: GreenFeed™

Measuring CH_4 of ruminant animals is difficult, especially in rangeland systems. Respiration chambers (RC) have been used over the past century to measure energy metabolism. For many years chamber systems have been the standard method for collecting CH_4 emission data because they are in a controlled environment but are not practical for a rangeland setting (Storm et al., 2012). Della Rosa et al. (2021) published a review of technical variations and protocols with different methods to measure CH_4 emissions. They defined RC as hood chambers (head box) and whole animal chambers. Respiration chambers have accurate measurements if successful gas recovery is performed. The problems with RC include not mimicking an animal's typical environment and affecting DMI. The studies below also used RC along with similar techniques that had comparable emissions measurement results (Della Rosa et al., 2021).

One such technique is using a sulfur hexafluoride (SF_6) tracer with free-range cattle. For this method to be successful, CH_4 released from the tracer must be known to accurately calculate the CH_4 released from the rumen (Storm et al., 2012). A few issues with SF_6 are that it is difficult to maintain a stable release of SF_6 in the tubes, inconsistency with CH_4 measurements that use chambers and SF_6 gas, and "background level determination," (Storm et al. 2012). SF_6 dilution rates are assumed to be identical to CH_4 (Johnson et al., 1994). Johnson et al. (1994) found that using the SF_6 method to be an unchallenging method to collected CH_4 emissions from livestock due to its low cost and ease of use. McGinn et al. (2006) used the SF_6 tracer, and the ERUCT technique with eight spayed beef heifers fed various diets to influence post-ruminal production of CH_4. The ERUCT technique places a permeation tube with SF_6 directly into the rumen with a Teflon membrane to control the gas release. They found that the ERUCT technique failed by day two for one of the heifers fed a high-grain diet. Further, McGinn et al. (2006) found that the ERUCT technique underestimated CH_4 emissions by an average of 4%. However, a general agreement exists that the ERUCT method is the best for range cattle, while those fed high grain diets (such as dairy operations and feedlots) had greater uncertainty (McGinn et al., 2006).

A newer technology available for the evaluation of enteric emissions (i.e., CH_4) is the GreenFeed™ Pasture System (C-Lock Inc., Rapid City, South Dakota). This machine can be deployed in a pasture with weaned animals and measure CH_4 fluxes in real-time. The animal is enticed with a pelleted feed to stick their head in the head box, and the machine collects its CH_4, CO_2, and O_2 emissions. Once the animal has visited, the emission data is directly uploaded to the web interface. Using this technology, animals can come and go as they please, and researchers can get multiple emission readings from their samples daily. The machine itself also auto-calibrates the sensors daily to help keep variation minimal.

Bes et al. (2022) used the GreenFeed™ system to collect individual emissions of CH_4, CO_2, and H_2 of Charolais growing bulls over two years (two independent groups of n=50-51 for a total of n=101) on two different total mixed rations (TMR). One group was fed a TMR of grass silage and high-fiber concentrate (GS-F), while the other half received a TMR of maize silage and high starch concentrate (MS-S). They also calculated DMI by collecting feed intake by weighing the feed troughs. Methane and CO_2 emissions were higher for the animals fed the TMR of MS-S on average. Gas flows in g/kg were also higher in the GS-F diets, but it was noted that, on average, the GS-F fed cattle had lower DMI (Bes et al., 2022).

Alemu et al. (2017) used crossbred heifers for a 2-week adjustment period before they collected residual feed intake (RFI) for 72 days. Residual feed intake is the measurement of feed efficiency from animals and are typically classified as either low-RFI or high- RFI animals. Heifers were fed ad libitum barley silage, steam-rolled barley, a supplement, and molasses; 16 out of the 98 cattle were randomly selected to have their enteric emissions collected using RC and GreenFeed™ systems. The heifers were split into two groups: low and high RFI. They found, on average, CH_4 emissions of the low group were 203 g/d, and for the high group, it was 222 g/d. Even though numerically different, there was no significant difference between the two groups ($P > 0.05$). They also found no significant difference when using the RC for the same two groups. Significant positive correlations between CH_4 and DMI and CO_2 and DMI were identified (Alemu et al., 2017). Further, the scientific literature supports a known correlation between enteric emissions and DMI (Johnson and Johnson, 1995; McGinn et al., 2006; Bes et al., 2022). Consequently, the increased interest in quantifying beef GHG and the importance of beef cattle on rangeland systems may have a silver lining as GHG quantification may help us answer a question that has been unresolved by rangeland livestock research for over three decades, which is how to calculate DMI for grazing livestock.

Objectives

Therefore, the objectives of our dairy C and DMI studies were to:

Carbon model objective:

1) Build and program a model to simulate soil carbon and flux with complex cover practices. We hypothesize that simulation results of complex cover will result in higher total soil carbon sequestration compared to conventional practices.

Enteric DMI model objectives:

1) Evaluate the relationship between methane (CH_4), carbon dioxide (CO_2), and oxygen (O_2) emissions and dry matter intake (DMI) of beef cows to develop an equation/model that predicts DMI from gaseous emissions for beef cattle grazing on rangeland. We hypothesize that cows consuming low-quality forage will produce more enteric emissions than those consuming moderate-quality forage.

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TABLES AND FIGURES

Table 1.1. Common cover crops for South Dakota (SD), Michigan (MI), and Wisconsin (WI).

SD	MI	WI
Annual Ryegrass[1]	Cereal Rye[1]	Badger Peas/ Oats Mix
Cereal Rye[1]	Italian Ryegrass[1]	Buckwheat
Common Vetch	Oats[2]	Crimson Clover
Cowpea	Oilseed Radish[1]	Daikon Radish[1]
Dwarf Essex Rapeseed[3]	Radish[1]	Dwarf Essex Rapeseed[3]
Field Pea	Red Clover	Medium Red Clover
Flax	Sorghum/ Sundangrass[2]	Ryegrass[1]
Oats[2]	Triticale[4]	Seven Top Turnip[1]
Pearl Millet	Turnips[1]	Triticale[4]
Radish[1]	Winter/ Spring Peas	Winter Rye[1]
Sorghum/ Sundangrass[2]		Winter Wheat
Turnip[1]		

[1]Cover crops shared for all states.
[2]Cover crops shared between SD and MI.
[3]Cover crops shared between SD and WI.
[4]Cover crops shared between MI and WI.

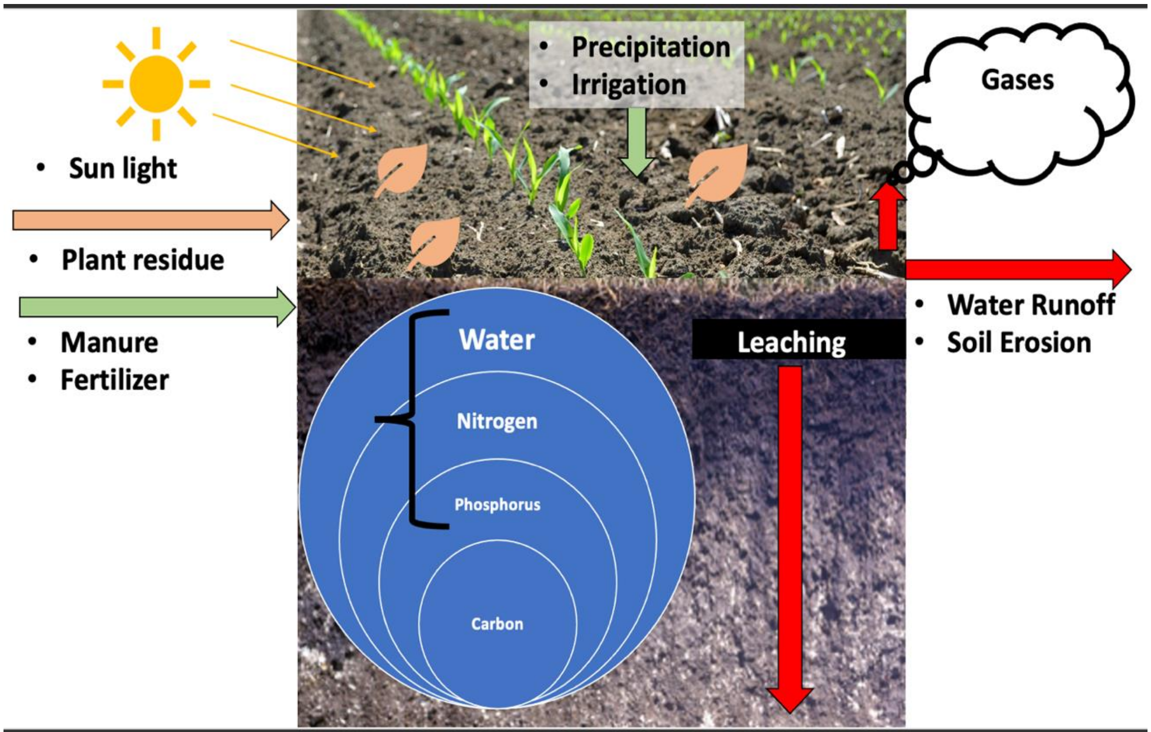

Fig. 1.1. Conceptual diagram of main soil and plant inflows, soil nutrient cycling, and outflows that impact agronomic production and the environment.

CHAPTER 2. SIMULATING REGENERATIVE COMPLEX COVER CROPPING PRACTICES ON MICHIGAN DAIRY FARMS TO EVALUATE DIFFERENCES IN SOIL CARBON SEQUESTRATION POTENTIALS

ABSTRACT

The use of regenerative agricultural practices is becoming more prevalent in the United States, especially in the dairy industry within the Midwest. Their use and adoption are being driven by topsoil and nutrient loss, rising production costs, and climate change concerns. The impact of dairy production on carbon (C) has raised concern from government, industry, and consumer sectors as soil organic carbon (SOC) can decrease or increase based on soil management. One regenerative farming practice that has potential to help increase SOC is complex covers (cover crops and intercropping). However, determining potential SOC sequestration is difficult especially regarding different tillage practices such as conventional (i.e., plow and disk) compared to conservation tillage (i.e., no-till). Simulation models can help evaluate regenerative farming practices that enable farmers to select high-leverage regenerative strategies that align with production goals and potentially increase SOC long-term. Therefore, the objectives of this study were to 1) modify the DAYCENT model to simulate soil C and flux with complex cover practices and 2) simulate different conventional and regenerative cropping management scenarios on United States dairy farms in Wisconsin and Michigan to assess differences in soil C. The Soil Carbon CareTaker model used parameters from DAYCENT that were modified to estimate SOC with different complex cover and tillage practices over 30 years for dairy fields (n = 12) within Michigan. The calibrated model was shown to lack precision

(R^2 = 0.07) but was highly accurate [mean bias = -0.26 (MB)]. After the model was determined to be reliable, we simulated a base case for each field along with four different scenarios: no-till (NoTill), 30 years of continuous corn (CornOnly), cover crops with tillage (CC), and cover crops with no-till (CC NoTill). The Michigan dairy fields were split into three different regions: west (n = 4), central (n = 2), and east (n = 6). Within these regions, we observed an average least percent soil C change from the base case of -14% (west), -12% (central), and -15% (east) for the CornOnly scenario, while the greatest average percent change from the base for each region was 350% (west), 361% (central), and 278% (east) for the CC NoTill scenario. Thus, the Soil Carbon CareTaker can be used as a tool for producers to assess regenerative management strategies that will enhance C sequestration, meet sustainability goals, and provide cost-effective regenerative dairy products to meet shifting consumer demands.

Keywords: Soil carbon, Cover crops, Complex covers, tillage, no-till, Modeling, Dairy.

INTRODUCTION

Background of United States Cropping Systems

In the United States, agronomic production systems are severely degraded by conventional farming practices, overgrazing rangeland, and the lack of knowledge regarding soil management (Pittelkow et al., 2015). The evolution of modern farming practices and technology has removed labor barriers, making it economically rewarding to convert native rangelands into row-crop production (Turner et al., 2018). Consequently, this land conversion to row-crop agriculture increases changes in hydrological patterns through soil erosion, causing decreased water quality via eutrophication and increased sediment load in streams and rivers (Bielders et al., 2003; Helmers et al., 2012). An estimated 75 billion tons of topsoil are lost worldwide annually, which causes an economic loss of ~$44 billion each year (Pimentel et al., 1995; Pimentel, 2006).The loss of soil productivity from degradation, decreased crop production, and increased erosion and eutrophication ultimately affect wildlife and humans who rely on healthy soils for food, animal feed, and fiber – all products essential for human life (Menendez et al., 2020).

Importance of Cropping in the Midwest

The Midwestern region of the United States contains over 363,164,895 ha dedicated to growing crops (USDA, 2021). Within Wisconsin (WI), Michigan (MI), and Minnesota (MN), there are 10,234,499, 1,126,442, and 6,984,874 ha dedicated to growing corn (*Zea mays*), soybeans (*Glycine max*), and spring/winter wheat (*Triticum aestivum L.*), respectively (USDA, 2021). Since these areas produce a large portion of the United States' crops, ensuring their long-term productivity and sustainability is vital.

Regenerative agricultural practices help producers build back healthy functioning soils instead of only preventing environmental degradation using conservation practices. Regenerative agriculture provides practices that help reduce environmental impacts such as erosion and eutrophication by building healthier soil that requires less fertilizer, is less susceptible to erosion, and ultimately improves crop production. This is a systemic fix, compared to practices like buffer strips that only reduce the unintended consequences of conventional farming (e.g., runoff; Menendez et al., 2020).

Regenerative Complex Cover Practices

Nurse Crops

Regenerative agricultural practices include nurse crops and cover crops. Nurse crops are planted with cash crops to help shelter and protect from weeds and undesirable plants. Alfalfa (*Medicago sativa*) is commonly planted with an annual plant like oats (*Avena sativa*) and peas (*Pisum sativum*) to suppress weeds and then are harvested together for more biomass. It has been shown that nurse crops do not affect the quality of forage in the seeding year when compared to an alfalfa field planted without a nurse crop (Hall et al., 1995). Although, nurse crops have been shown to restrict alfalfa growth in years with below-average precipitation (Hall et al., 1995). Since alfalfa is a perennial, using it for a cover crop is not a popular practice for many producers, but it is commonly interseeded with other crops. An example of this is a producer planting a forage grass mix such as tall fescue (*Festuca arnudinacea*), timothy grass (*Phleum pratense*), and meadow fescue (*Festuca pratensis*) to improve yield, persistence, and nutrients in their alfalfa hay crop. Oats also may be planted as a nurse crop but then are typically chopped and ensiled to be used as feed for cattle.

Cover Crops

Cover crops are defined as crops grown to protect the soil when no cash crops (i.e., primary crops such as corn) are grown (SWCS- U.S., 1994). Cover crops can benefit producers by protecting soil from wind and water erosion, improving organic C and water infiltration, and reducing nutrient leaching (SWCS- U.S., 1994). For example, Franzlubbers et al. (2021) demonstrated that cover crops increased cumulative C mineralization by 9% when multispecies cover crops were planted, compared to no cover crops (control). They also found that particulate organic C and particulate organic nitrogen (N) were increased by 4% and 5%, respectively, when multispecies cover crops were compared to the control (Franzluebbers et al., 2021). Although cover crops are generally used to improve soil health, they can also be used for other factors, such as wildlife habitat, extending the winter grazing period for cattle, and preventing weed growth. Legume cover crops can add extra N to the soil through symbiotic N fixation (Mylona et al., 1995). Interseeding crops is another technique that producers can use to establish cover while the primary crop is still growing (Youngerman et al., 2018). Many benefits come from intercropping, including reduced nitrate (NO^{-3}) leaching, an increased growing period by establishing growth earlier in the season, and maximized biomass cover.

Complex covers also work to improve soil health. Soil microbes and fungi cycle C, N, and phosphorus (P) by transforming (e.g., nitrification and denitrification) minerals in the soil (Aislabie and Deslippe, 2013). They also recycle wastes and detoxify soils with mineralization and immobilization (Aislabie and Deslippe, 2013). Nitrogen, P, and potassium (K) are the essential macronutrients in the soil to help crops grow and are common fertilizers used in cash crop operations (Malghani et al., 2010). However, many years of N application can negatively affect the cycling microbes (Shen et al., 2008; Hallin et al., 2009), but there haven't been many studies on the effects on microbes from continuous P and K fertilizer use (Pan et al., 2014).

Cover Crop Demand in the Dairy Industry

Given the growing demand for regenerative cropping systems to inset and offset C and mitigate adverse environmental externalities, the United States dairy industry is particularly interested in cover crops. For example, MI has many dairy farms, creating a precedent for adapting the use of cover crops into these operations. Rye, oats, red clover, and radish are the most common unharvested cover crops. Some MI producers also utilize typical cover crop plants, such as oats/field peas or triticale/field peas, forage sorghum, sudangrass, or a sorghum-sudangrass to fill gaps during cash crop seasons to be grown as feed to be ensiled or fed to their dry cows/heifers (Cassida, *personal communication, September 2021*). However, interseeding is a rare practice for MI producers as alfalfa and crops such as oats, timothy grass, tall fescue, and meadow fescue are used for increased biomass for ensiled feeds on dairy operations (Cassida, personal communication, September 2021).

Another proponent of regenerative practices in the dairy sector is the rapidly decreasing number of producers relative to the increasing size of operations (USDA, 2022). States noted for this shift include WI and MI, which produced approximately 14 and 5 million kg of milk, respectively in 2020 (USDA-NRCS, 2021). As a result of this shift, the practice of holding cows in large barns/lots has become a widespread practice to manage growing dairy cow herd numbers effectively. Consequently, grazing has become uncommon, resulting in producers having to either increase feed production or purchase feed to provide for their cows in concentrated animal feeding operations (CAFO). Further, milk prices have been fluctuating, which causes risk for producers' income despite costs, like feed, remaining constant (USDA-NRCS, 2021). These financial constraints are amplified by environmental concerns about water and air quality, water runoff, sediment loading, soil erosion, and NO^{-3} leaching from urine (Rotz et al., 2009). These concerns have accelerated the utilization and consideration of regenerative agricultural practices, such as cover crops, as a systemic solution for environmental and economic benefits.

Using Models in Dairy to Inform Greenhouse Gas Mitigation and Carbon Sequestration

The continued accumulation of GHG has raised global concern for industries like agriculture, which have become subject to major political and societal pressure for products that reduce GHG emissions and improve C sequestration. With the help of models, we can estimate what agricultural practices are the best for reducing environmental concerns while maintaining or decreasing costs without waiting an extended period to determine differences. Models are a critical decision aid for the dairy industry to evaluate science-based practices recognized to improve soil C sequestration and mitigation, aligning with Scope 3 and the Science Based Target Initiative (EPA, 2023; WRI, 2023) for insetting and offsetting standards. For example, one of the most prominent cereal grain and dairy suppliers is General Mills Inc. which has made a goal of having ~404,686 ha dedicated to regenerative agriculture and sustainable dairy products by 2030. However, managing a dairy operation is highly complex because of the interconnections between animal, manure, soil, and stored crops with their performance standards. Further, dairy producers must reach animal growth and performance requirements and manage manure storage capacity and quality (chemical composition), soil and crops for growth and environment, and maintain correct grain storage quality and availability/time (Kebreab et al., 2019). Although regenerative practices can improve these components, it is impossible to do all methods simultaneously and realize production or financial success. Thus, we need models to help evaluate different regenerative management practices to identify the best regenerative strategies that align with farmer goals while avoiding detrimental or ineffective ones. Identifying strategies for GHG mitigation and C sequestration on agricultural lands is difficult because it takes a long time to detect a change and account for actual mitigation and sequestration quantities due to the inherent fluxes. Modeling C is important because it can show us the likely future and teach us valuable lessons on managing C in our soils and atmosphere.

Agriculture Carbon Models Overview

Many field-level models exist for evaluating soil C, such as the Soil and Water Assessment Tool (SWAT), Denitrification-Decomposition model (DNDC), Agricultural Production System sIMulator (APSIM), and the Integrated Farm System Model (ISFM) (Zhang et al., 2013; Jiang et al., 2017) which differ in trade-offs and capabilities. Aside from these another well known model used for assessing soil C is the CENTURY model.

The CENTURY model has a four-pool SOM sub-model for C, N, P, and sulfur (S). The accumulation or loss of each pool is based on SOM turnover rate and decomposition characteristics at a 20 cm soil depth. This model utilizes different plant-soil ecosystems to represent C and nutrient changes in a particular system (Kelly et al., 1997). The CENTURY model eventually led to the development of the DAYCENT model. The DAYCENT model is a terrestrial ecosystem model that simulates C, N, and trace gas exchanges among the atmosphere, soil, and vegetation (Parton et al., 1987; Del Grosso et al., 2001). The difference between the two models is that the CENTURY model has a monthly timestep, while DAYCENT is daily. Additionally, the DAYCENT model simulates natural/agronomic events, such as fire, cultivation, and grazing, while estimating plant growth. The DAYCENT model can more precisely simulate plant residue and root decomposition, flows of nutrients, soil water, and the temperature of the soil compared to the CENTURY model (Del Grosso et al., 2001).

The growing demand for sustainable dairy production systems that inset/offset carbon, increase production, reduce costs, and lead to increase marketability (e.g., market premiums) has accelerated the role of modeling C on single farms and supply sheds. Using models to select the highest leverage decisions while avoiding unintended consequences helps farmers maintain or improve production while improving soil health. Further, it is likely that without SOC complex cover simulation models capable of determining the potential carbon sequestration and mitigation, that the effective use of regenerative practices will remain challenging. Therefore, the objectives of this study were to 1) modify the DAYCENT model to simulate soil carbon and flux with complex cover practices and 2) simulate different conventional and regenerative cropping management scenarios on United States dairy farms in WI and MI to assess differences in soil C.

MATERIALS AND METHODS

Complex Covers Model

Study Area

The study areas included the University of Wisconsin-Madison Wisconsin Integrated Cropping Systems Trial (WICST) located in Arlington, WI, and General Mills Inc. dairy pilot farms throughout MI. We used 30 years of field trial data for tillage, harvest, and OM from the WISCT dairy forage research trial (-43°18'9.47" N, -89°20'43.32" W). The average high temperature for July is 27°C, and the average low for January is -10°C (Weather-US, 2023), with an average precipitation of 86.92 cm a year (US Climate Data, 2023a). The land in this area is described as fertile prairies with gentle slopes and minimal trees (Engel and Hopkins, 1956). The dominant soil types for these areas are Alfisols and Histosols. The second study area included different regions of Michigan; specific locations were intentionally omitted for producer confidentiality. The sites fall along the longitudinal line between 83°-85° W and move on an east-to-west gradient (roughly 43° 30' 18.8388" N, 83° 23' 22.0596" W; 43° 38' 55.536" N, 84° 46' 1.38" W; and 43° 35' 49.4376" N, 85° 57' 53.7732" W). These areas have temperatures ranging from a high of 28°C to a low of -10°C in July and January, respectively (US Climate Data, 2023b; US Climate Data, 2023c; US Climate Data, 2023d) and a precipitation range of 82.14-88.16 cm (US Climate Data, 2023b; US Climate Data, 2023c; US Climate Data, 2023d). The dominant soil type for these areas is Alfisols, with Histosols being the second most prevalent soil type (Sommers, 1977). These areas are primarily dominated by dairy farms that grow crops to feed their livestock. We developed the model once data was collated from these different study areas.

Model Development

To build and program a model to simulate soil C (kg/ha or %) and flux (kg/day) with complex covers, we followed the five steps outlined by Sterman (2000). The five steps included 1) problem articulation, 2) conceptual mapping, 3) model formulation, 4) model calibration and testing, and 5) policy design and analysis (Sterman, 2000). The first step of problem articulation defines the purpose of the model, identifies the critical key variables, defines a timeline, and looks at the past behaviors of the problem (i.e., soil carbon and flux). Specifically, the model aimed to predict soil C sequestration based on different cropping and management practices over 30 years. Key variables were identified through an extensive literature review, and we were able to obtain long-term SOC data from scientific research studies *(see Methods; step four).* Step two included developing a conceptual map of the model, which was developed using different diagrams, maps, and tools regarding C flux (Fig. 1 and 2; Del Grosso et al., 2001). The model boundaries were used to determine the fundamental variables for the model while under development; also, they indicated what variables should be omitted from the model (Menendez et al., 2023). Our model boundary process was guided by existing soil C models with reliable equations and parameters (Neitsch et al., 2011; Parton et al., 1987; Del Grosso et al., 2001).

Step three consisted of formulating the mathematical model (i.e., the Soil Carbon CareTaker) with known mathematical equations for simulating SOC dynamics. For the current study, we utilized parameters from the DAYCENT model (Delgrosso et al., 2001; Parton et al., 1987). The SOC component of the DAYCENT carbon model was adapted into Vensim DSS™ (Ventana Systems Inc., 2015), a visually based dynamic modeling software (Fig. 1 and 2). First, we adjusted the weekly coefficients for soil C decomposition [K1 = structural decay rate (0.076), K2 = surface residue decomposition rate (0.28), K3 = structural decay rate (0.094), K4 = metabolic decay rate (0.35), K5 = active SOM decay rate (0.14), K6 = slow SOM decay rate (0.0038), K7 = passive SOM decay rate (0.00013)] reported by Parton et al., 1987 to daily coefficients by dividing each K value by 7. Once the model was replicated on a daily timestep, we added additional functionality to the model to achieve our purpose of daily SOC and CO_2 flux. Adding the functionality for incorporating complex cover practices in the Carbon Caretaker model required specific coefficients for different crop types and agronomic practices, including yield, stubble and root fractions, and nutrient content (Table 2).

To obtain total biomass for crops at harvest, we used average harvest yield (kg/ha) that was collected from WISCT, and harvest efficiency (dmnl) values derived from running SWAT simulations for each crop across 30 years (Neitsch et al., 2011; equation 1).

$$(1)\ \text{Total Biomass} = \frac{\text{Harvest Yield}}{\text{Harvest Efficiency}}$$

Where total biomass is the amount of vegetation produced above and below ground, before harvest (kg/ha) and harvest yield is the amount of the above-ground vegetation that is harvested (kg/ha), and harvest efficiency is the fraction of the total plant that is harvested (dmnl).

Stubble and root fractions are essential for the model because the standing dead plants and roots add carbon to the soil at different rates and levels and are split into either structural or metabolic material based on the lignin (L) and N content of the plant residues (Table 2).

Next, we used SWAT-derived root fractions to estimate the total biomass remaining in the soil as roots (Table 2; equation 2).

$$(2)\ \text{Root Biomass} = \text{Total Biomass} * \text{Root Fraction}$$

Where root biomass is the living roots below ground (kg/ha), and root fraction is the amount of dead roots that are incorporated into the soil (dmnl).

Stubble residue was derived by multiplying the total biomass by the stubble fraction (Equation 3):

$$(3)\ \text{Stubble Residue} = \text{Total Biomass} * (1 - (\text{Harvest Efficiency} + \text{Root Fraction}))$$

Where, stubble residue is the above ground biomass from the plant left behind after harvest (kg/ha).

For annual crops (e.g., corn), stubble, residue, and root biomass were only incorporated in the season's last (and only) harvest. For mixed species (i.e., alfalfa and oats), stubble residue was incorporated at the last harvest, but only 50% of the root biomass was incorporated to account for annual crop roots, while perennial crop roots were assumed to remain in the soil until the final harvest (i.e., they were still living). At the time of final harvest (e.g., termination of an alfalfa crop), 100% of the root biomass was incorporated. This decision rule was derived using the Vensim DSS™ optimization tool to assess differences in the proportion of roots incorporated. Simulations that exceeded the "50% at last harvest rule" resulted in extreme and unrealistic amounts of soil C additions.

Crop-specific factors included L and N (%) for corn, alfalfa, oats, rye, peas, winter wheat, and hairy vetch and were collected from NASEM (2016) and Van Soest (1994). For mixed species plant covers (i.e., complex covers), we calculated the averages between the species because individual biomass data for each plant type and its associated L and N content is not available in the literature and varies for each field, year, and planting rate. The L and N percentages are essential because of the nutrients each provides which regulate the partitioning of plant material into structural and metabolic carbon (NASEM, 2016; Van Soest, 1994).

Agronomic Practices

The tillage mixing efficiency factors reported in SWAT were used for each cultivation implemented (Neitsch et al., 2011). The tillage mixing efficiency served two purposes, the first was to incorporate crop residue from above-ground to below-ground C, and the second was to impact active, slow, and passive (1-5 yr., 20-40 yr., and 200-1500 yr. cycling; Parton et al., 1987) decomposition rates, known as the tillage decomposition multiplier. Within the model, mixing efficiency was used to account for the impact of no-till to conventional-till, using the range of 0.05-0.85 (dmnl), respectively. In terms of altering the decomposition rates of soil C with the carbon decomposition multiplier, we set the minimum value at 1 (dmnl) and max value at 15 (dmnl) according to parameters recommended in the DAYCENT model (Del Grosso et al., 2001; CSU, 2012). After a tillage event, our model used a fixed delay to account for tillage impacts on active, slow, and passive soil C decomposition rates over 30.5 days for each tillage event (CSU, 2012).

Other model input data included weather data [precipitation (mm), minimum daily temperature (˚C), maximum daily temperature (˚C), and average ambient temperature (˚C)]. A latitudinal approximation of solar radiation (ra; MJ/d) was also incorporated using the Hargreaves method (Rodriguez-Iturbe et al., 2001). Lastly, soil bulk density (g/cm^3) and the silt-clay fraction (dmnl) were also collected from Web Soil

Survey (NRCS, 2019) for the WISCT study area. Bulk density and soil depth were used to convert significant inflows and outflows (i.e., active, slow, and passive soil C) to %C (Fig. 3). Like the DAYCENT model, the Soil Carbon Caretaker model only accounted for one soil depth (cm) set by the user (e.g., 20 cm depth). The collected data was then organized into an Excel file by Julian date. The collated data was then imported into Vensim DSS.

Step four tested how the model behaved under extreme conditions and how sensitive it was to different parameter changes, and then the model was calibrated to see if it could replicate observed historical data (i.e., SOC data at 15 cm depth). We systematically tested vital input variables and coefficients (Table 2). For example, yields were set to zero and increased to 10 times average amounts to see if the model equations adequately handled these conditions. We also ensured that the model obeyed the laws of physics by not double accounting or creating matter. For example, we cannot have negative C in the soil, and we tested each carbon pool, such as above-ground structural and metabolic carbon, to make sure their masses matched with above-ground residue, i.e., the structural and metabolic C should not exceed residue under normal circumstances.

Another example is when we pushed biomass to 1,000,000 kg to see if the equations were robust enough to handle extreme amounts of biomass input. Conversely, we tested zero biomass inputs to ensure the C flux values would flatline. Furthermore, we tested the sensitivity of the model to critical parameters such as the silt-clay fraction (e.g., 0.5-0.91) and tillage decomposition multiplier (1-15), because these are known factors that should cause SOC to change within the model (Parton et al., 1987; Del Grosso et al., 2001). We calibrated the model after the model equations were tested and found adequate.

Model Calibration

The model calibration specifically compared simulated SOC (%; i.e., active plus slow carbon) and observed SOC from the WICST dataset. Model calibration aims to make sure that it can simulate reality, in our case, SOC changes across decades from specific agronomic practices. Our observed SOC data was derived from SOM using the 0.58 conversion factor (Miller and Gardiner, 2000). Specifically, we used the alfalfa+ oats-alfalfa-corn rotation from 1990-2018 (treatment identification was R5, treatment 11, and plots 110, 208, 304, and 413) because this treatment represented a complex cover type (i.e., oats and alfalfa grown simultaneously), which suited the purpose of our model (University of Wisconsin, 2023). The R5 treatment also had extensive and detailed agronomic management data, which included crop planting dates, harvest dates, harvest yield (kg/ha), tillage dates, and tillage practice type (e.g., disk plow, chisel plow, and harrow tines), which are representative of conventional dairy forage production systems.

The model was calibrated using four initial input variables: initial active C (kg/ha; parameter range = 500-30,000), initial slow C (kg/ha; parameter range = 500-30,000), initial passive C (kg/ha; parameter range = 250-500), and decomposition multiplier value (dmnl; parameter range = 1-15). To calibrate our model, we used the optimization function within the Vensim DSS program, which automated our calibration using the four variables identified above. Forty-nine simulations were run to find the optimal values for each variable and maximum payoff (i.e., the minimum distance between observed and predicted SOC). Parameter ranges for optimization were checked to ensure that the model achieved a good fit using realistic values, which is a concern using automated calibration (Menendez et al., 2020). Calibrating the model to initial active C, initial slow C, initial passive C, observed C, and predicted C gave us the maximum payoff at 30,000(kg/ha, 30,000 kg/ha, 250 kg/ha, respectively, and the C decomposition multiplier was 15.

To ensure our model calibration was adequate, we ran the output of observed and predicted percent soil C in the Model Evaluation System (MES; Tedeschi, 2006) to determine levels of accuracy [mean bias (MB)] and precision (R^2) results. The MB results suggest the difference between the observed and predicted values (values closer to 0 being better). While R^2 measures the level of precision between the observed and predicted values, with values closer to 1 being more precise (Menendez et al., 2020). We also screened for systematic errors using Theil inequality statistics for root mean square error of prediction (RMSEP) decomposition. The RMSEP calculates the distribution of the unequal mean, variance, and covariance and is an indication of structural adequacy (Menendez et al., 2020). After model calibration results were deemed adequate, we were confident that the model could reliably simulate C sequestration in the soil under different management practices or "what if" scenarios that included complex covers.

Dairy Cropping Scenarios

Step five included a series of "what-if" policy questions or model scenarios that compare all changes in soil C and flux to the base scenario. We evaluated 12 dairy farms in MI using the General Mills Inc. data, which came from the state's western, central, and eastern regions. The dairy farms are part of a pilot program through General Mills Inc. to evaluate SOC and regenerative agricultural practices (e.g., complex covers). The 12 dairy pilots selected were a subset of the total pilot farms representing a spectrum of cropping practices across different soil types, crops, management, and climate. This enabled us to evaluate a broad range of existing SOC levels and their potential changes relative to previous management practices. General Mills Inc. baseline soil sample data included: beginning depth (cm), ending depth (cm), bulk density (g/cm^3), 1N KCI-Nitrate (ppm NO_3-N), 1N KCI- Nitrate (kg/ha N), 1N KCI-Ammonium (ppm NH_4-N), 1N KCI-Ammonium (kg/ha N), total organic C (%), total C (%), total inorganic C (%), soil sand (%), soil silt (%), soil clay (%), total organic C (kg/m^2/core depth of 30 cm), total inorganic C (kg/m^2/core depth of 30 cm), and total C (kg/m^2/core depth of 30 cm). For this study, we focused on the beginning depth (cm), ending depth (cm), bulk density (g/cm^3), total organic C (%), total C (%), total inorganic C (%), soil silt (%), and soil clay (%) at a uniform depth (kg/m^2/core depth of 30 cm).

Historical production data from the pilot farms was not available to warm up the Soil Carbon CareTaker model, so we used the WISCT calibration scenario as our baseline for the MI dairy farms. This is because the WISCT scenario (i.e., WISCT base) included real tillage practices, cropping management, and SOM sampling for dairy forage systems over 30 years. After the WISCT base was simulated, we ran four additional scenarios to determine potential changes in SOC for each field (i.e., the WISCT base was run in WI and included the four scenarios and then the same WISCT base and four scenarios were applied to MI fields and their respective conditions). The scenarios included: 1) no-till (NoTill), where the tillage mixing parameter was changed to 0.05 for tillage incorporation for each tillage event; 2) corn only (CornOnly) that simulated continuous corn for 30 years and used the corn cropping practices (tillage, harvest dates, average harvest yields) in the WISCT-base case; 3) cover crops with conventional tillage

(CC) where additional biomass was added in as stubble and roots to simulate biomass from cover crops and practices were the same as the WISCT-base; and 4) cover crops and no-till (CC NoTill) which was the same as the CC scenario except that tillage event values were changed to 0.05 for tillage incorporation (i.e., tillage mixing efficiency value). The cover crops chosen for this study were a winter wheat and hairy vetch mix. These two plants were selected for their common use in cover crop mixes for the area, their ability to be planted late in the season, and not winter kill. In our study, the cover crops were planted after the last tillage date for CC (September – November) and incorporated as roots and stubble with tillage before planting in the spring (April- May). We used the same cover crops planting and harvest dates for our CC NoTill, but the only difference was that they were not incorporated with tillage in the model.

The same base case (formerly stated as WISCT base) and what-if scenarios were run for the Michigan fields (n =12), and within these fields, soil silt plus soil clay ranged from 23-68%. The fields were separated into three different regions: west (n = 4), central (n = 2), and east (n = 6). Temperature, precipitation, and soil silt plus clay % were similar within the regions (Table 3).

Model warm-up included initializing each pilot farm's initial soil C using actual SOC and SIC values (i.e., total organic C + total inorganic C collected for each pilot farm). To calculate initial active soil C and initial slow soil C, we used the collected total organic C and divided it by two (i.e., 50% was partitioned to each initial pool). The broad range of total C that was reported for fields (n = 9) with regenerative cropping practices was 1.05-5.08% and the conventional cropping fields (n = 3), which was 1.22-1.61%.

RESULTS

Calibration Site

Our calibration statistics results for precision, accuracy, and screening for systematic errors resulted in an adjusted R^2 of 0.07 and MB of -0.26, indicating that the model had deficient levels of precision but was accurate and suitable for our purposes (Fig. 3). The Theil statistics resulted in an unequal mean, variance, and covariance of 59.60, 13.53, and 26.88%, respectively, indicating no systematic errors. For our WICST calibration study area (i.e., oats/alfalfa-corn dairy forage rotation,) the CC-NoTill scenario added the most SOC compared to the base case (Table 4).

Michigan Dairy Farms

The region's average observed soil C percentage for west, central, and east were 0.86, 0.82, and 1.23%, respectively. Soil C had the least change from the CornOnly scenario across all regions from the base case, typically resulting in decreased SOC from the base case. Soil C (%) had the most significant change from the base using the CC NoTill scenario, with a 361% average increase in soil C in the central region compared to the other regions (Table 5). On average, the NoTill and CC increased soil C above the base case by 105% and 200%, respectively, across all simulated pilot farms.

We ranked soil C change from the lowest to highest percentage based on percent soil silt plus clay, because the model was sensitive to this parameter (Parton et al., 1987). Overall, the CornOnly scenarios had the smallest change from the base case with no trend relative to the silt plus clay parameter (Table 6). However, as soil silt + clay percentages increased, the percent change from CC NoTill from the base case decreased (Table 6).

DISCUSSION

Measuring soil C is vital for successfully adopting regenerative agricultural practices in dairy operations because it indicates healthy functioning soils and carbon sequestration. Simulating soil C using models helps estimate the effectiveness of different regenerative practices relative to conventional options. Selecting appropriate regenerative practices has the potential to help dairy farms to satisfy pressure from governmental regulations and consumer demands for more sustainable products that reduce negative impacts (GHG and climate change) from agriculture (Rochette et al., 1991) by modeling expected soil C sequestration (e.g., insetting) at a field level.

Soil Carbon CareTaker

Calibration

Our model lacked precision (R^2) because the specific dates that C was sampled in the WICST are unknown (Fig. 3); thus, our model predictions of soil C could not be subsetted for specific sample days when observed values were taken. Due to inherent seasonal fluxes, adequate representation of soil C has been difficult for SOC reporting (active and slow) (Lal et al., 2003; Parton et al., 1987; Del Grosso et al., 2001). Since the interannual variation of soil C occurs (i.e., carbon flux), future studies should most likely report and, if possible, sample at known periods of low and high C (within a year) and use this average to represent C storage.

During the model calibration process, a significant limitation was the partitioning of the active and slow soil C. The dynamic relationships within the model would overcompensate for one or the other if these soil C pools were not initialized in equilibrium (Parton et al., 1987). Within our field datasets (WICST and pilot farms), we did not have separate measurements of active and slow C. Thus, we maintained the 50-50 split for the initial levels of active and slow C (kg/ha). Future research should be conducted to determine these C fractions and improve model coefficients that govern the transfer of soil C between active, slow, and passive pools (Blair et al., 1995). Accounting for C transfer into different C fractions like mineralized C becomes even more complex when considering soil depth and heterogeneous soil types within a field. Organic C is also less mineralized under conservation tillage practices because it is protected (Rovira and Greacen, 1957). Determining how best to account for and model changes to these C pools requires a more detailed analysis of C pools during pre-and-post soil sampling. Other model limitations included a lack of data for root biomass for different crops and L/N content of residues (including roots). Thus, the next step is determining the proportion of root sluffing and L and N fractions relative to specific plants within complex cover mixes. Collecting the fraction of roots and L and N fractions for multispecies plant cover would strengthen the Carbon CareTaker model's ability to estimate SOC.

Management of Soil Carbon and Complex Cover Data

A significant limitation of this study was collecting data for multiple decades with factors such as OM, crop rotations, harvest yields, and tillage practices. For example, we preferred the WISCT data because it contained 30 years of detailed agronomic cropland management records (University of Wisconsin, 2023). For instance, we had to convert SOM to SOC by taking SOM and multiplying it by 58% (i.e., 0.58) to get a converted SOC for our model. This is because usable long-term soil C data is rare throughout the United States. Even if long-term SOC data is available, farm records are not often collected and stored in a usable digital format to calibrate models (historical data), limiting the ability to run predictive simulations. Consequently, data processing and storage was the biggest challenge in building and organizing our model. Organization of the input data was critical to make sure that different fields and scenarios were accurately represented. Further, repeatable, transparent, and well-documented models build end users' confidence (Menendez et al., 2020). To expedite our simulations while maintaining data quality and model transparency, we developed a Shiny App to automatically collect our weather and soil data (McFadden et al., 2023) using spatial field data files (e.g., KML). Further, the Soil Carbon CareTaker model is also linked to the App and can be used online for farms within the contiguous United States. Thus, an opportunity exists to more efficiently integrate on-farm data into decision support tools such as the Soil Carbon CareTaker model using automated online platforms, the Internet of Things (IoT), remote sensing, and big data analysis (Menendez et al., 2020; Jacobs et al., 2022; Brennan et al., 2023).

Scenario Performance

After the simulation of the dairy pilot farms from MI for all scenarios, we saw that the scenarios NoTill, CC, and CC NoTill performed as we had expected. Interestingly, CornOnly followed that trend except for passive soil C.

Corn Only Scenario

It has been reported that continuous corn with conventional practices will decrease soil C amounts, and this aligns with our current study except for passive soil C (Havlin et al., 1990; Clapp et al., 2000; Reicosky et al., 2002). Continuous corn rotations have been shown to maintain or decrease SOC over 13 years (Clapp et al., 2000). This study also evaluated the effects of returned or harvested stover and N fertilizer and indicated that SOC storage was extremely sensitive to tillage. Further, all management practices tested in this study did affect the amount of corn residue that turned to SOC (Clapp et al., 2000). Similarly, Riecosky et al. (2002) did a study on a 30-year continuous corn field that was tilled with a moldboard plow and found that soils became a C source while the moldboard plow was being used as an agronomic practice (Reicosky et al., 2002). Surprisingly, in the current study, passive soil C increased much more than the other scenarios, which is not what we would have expected for continuous corn. Therefore, this is likely a model limitation and merits further investigation.

No-Tillage Scenario

Like other studies, the current study indicated that soil C increased from regenerative agricultural practices such as no-till (Ussiri and Lal, 2009). For example, Ussiri and Lal (2009) compared three different tillage practices: moldboard plow, reduced till, and no-till for a corn field in Ohio. No-till fields held twice as much C within samples from 0-30 cm, although only samples from 0-15 cm had significantly more SOC for no-till than the other two practices. The Soil Carbon CareTaker also estimated that no-till practices over 30 years could increase soil C by 125% above the base case. No-till practices have significantly impacted SOC more than crop rotations (Gál et al., 2007). For example, within the first 0-15 cm of soil, no-till had a significantly higher SOC than cropland managed using conventional tillage practices in Indiana (Gál et al., 2007). Further, DAYCENT model simulations have indicated that crop fallow rotations and conventional tillage reduced SOM significantly (Del Grosso et al., 2001). One study disagreed with our findings regarding no-till; their research found that no-till does not favor C sequestration over 20 years (Sanford et al., 2012). However, it should be noted that no-till was not the lone practice in this study, and these other practices may have also affected SOC sequestration.

Cover Crop Tillage Scenario

Abdalla et al. (2014) used DNDC to compare reduced tillage and cover crops to conventional tillage and cover crops. They saw an increase in SOC with cover crops and tillage (0.20 mg C/ha/y) compared to conventional tillage (-0.30 mg C/ha/y). However, unlike the current study, it was reported that there was a larger increase in SOC at the beginning, and then SOC accumulation started to plateau within 20 years (Abdalla et al., 2014). In contrast, our simulation results showed a slow increase in soil C over 30 years when implementing cover crops. This may indicate that our model lacks a feedback relationship that limits SOC accumulation rates as soils reach a maximum SOC storage capacity. Evaluation of cereal rye and annual ryegrass increased SOC compared to Austrian winter pea, hairy vetch, and canola cover crops (Kuo et al., 1997), which is in alignment with our study. We believe this is because rye created more biomass, a primary driver of SOC accumulation, than shorter crops like peas, hairy vetch, and canola, but further investigation is needed at the field level.

Cover Crops No-Tillage Scenario

Our model simulated the most soil C increase under the CC NoTill scenario for all fields. This is likely because this scenario had increased residue that was allowed to slowly decompose into the soil rather than being more rapidly deteriorated from tillage activities. The soil decomposition multiplier function (Del Grosso et al., 2001) adjusted the impacts of tillage on soil C decomposition within the Soil Carbon CareTaker model.

However, more work is needed to determine adjusted rates of soil C decomposition or incorporation relative to specific tillage implements or lack thereof. Since tillage is highly correlated with the loss of SOC to atmospheric CO_2, it is understandable that no-till would increase SOC. Many studies have observed increased SOC with cover crops and no-till (Sainju et al., 2002; Varnel and Wilhelm, 2010).

Further, our study indicated that mixed species cover crops have the potential to increase SOC faster than a particular cover crop. In the Great Plains, a spring triticale cover crop increased SOC by 2.8 MG/ha (Blanco-Canqui et al., 2013). Furthermore, another study stated that the use of cover crops and no-till not only maintained the SOC from the baseline from a 12-year period but increased SOC, which led to the conclusion that cover crops and no-till agronomic practices are viable strategies to sequester SOC (Olson et al., 2014). Thus, additional scenarios comparing single and multiple cover crops are warranted, especially as more specific yield and L/N data are obtained. Further, this should include the alteration of soil nutrients effects on crop production which in turn influence residue/root availability and nutrient composition in each field (i.e., dynamic soil properties) (Hughes et al., 2023; Zhang et al., 2021).

The current study did not account for root crops, and this is a significant next step since cover crop mixes established earlier in the year include root crops that help to decrease soil compaction. For example, a study that used the DNDC to forecast SOC levels until the year 2050 used variations of manure management, tillage practices, winter cover crop, and crop rotation (Bierer et L., 2021). The SOC was simulated well using the default DNDC model, although the default and calibrated DNDC models had a sizeable absolute error when different manure applications were simulated. It was estimated that the SOC in a rotation of wheat-potato-barley-sugar beet did not significantly change in eight years without the effects of manure (P = 0.905) (Bierer et al., 2021). Notably, though the default in DNDC provides a reference for users in a similar region, overestimation of SOC sequestration is possible. This overestimation is likely due to the lack of model equilibrium for the desired simulation period (Bierer et al., 2021). Thus, the Bierer et al. (2021) study can help users calibrate DNDC with their data so it can counteract potential overestimations.

Carbon Flux

In our study, we saw that CC had the most change, on average, from the base (0.42%) when observing the total daily CO_2 fluxes compared with other scenarios. While CC NoTill, on average, had the least change from the base (0.34%) (Table 7). Another study indicated that tillage has a significant effect on CO_2 emissions in the short term but also showed that CO_2 emissions for the growing season are affected by crop rotations (Omonode et al., 2007). Thus, CO_2 flux into the atmosphere should continue to be evaluated to tell the entire sequestration story relative to additional atmospheric contributions. This is important because of the concern with GHG emissions from policymakers and the public, who have a growing interest in regenerative agriculture.

Overall, our addition of complex cover capabilities to the DAYCENT model aligns with known changes from regenerative practices and is a reliable tool for evaluating potential SOC and flux changes. Similarly, modifying the DAYCENT models' ability to incorporate complex covers in a rapid, transparent, and repeatable manner helps advance the assessment of SOC relative to regenerative agronomic practices. The use of participatory farmer-scientist modeling efforts will be essential as dairy farms continue to consider adopting practices like complex cover crops and for the documentation of potential soil health and C changes.

CONCLUSION

In conclusion, we successfully modified DAYCENT to reliably estimate soil C for different cropping scenarios, specifically complex covers. Using the model, we confirmed that adding complex cover crops and no-till practices increased soil C by an estimated average range of 194- 422% for the MI dairy pilot farms. The current study also identified important limitations regarding observed long-term soil C data and the barriers to integrating farm management data (e.g., planting and tillage). Going forward, additional data and automated collection methods are likely to dramatically enhance the ability of SOC models to estimate changes relative to different complex covers and dairy farmland management practices. Therefore, the Soil Carbon CareTaker can be used as a tool for producers to assess regenerative management strategies that will enhance C sequestration, meet sustainability goals, and provide cost-effective regenerative dairy products to meet shifting consumer demands.

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TABLES AND FIGURES

Table 2.1. Most common cover crops for Michigan (MI) and Wisconsin (WI).

MI Cover Crops	WI Cover Crops
Cereal rye	4010 badger peas/oats mix
Italian ryegrass	Buckwheat
Oats	Crimson clover
Oilseed radish	Daikon radish
Radish	Dwarf essex rapeseed
Red clover	Medium red clover
Sorghum/ sundangrass	Ryegrass (teyraploid, annual, or Italian)
Triticale	Seven top turnip
Turnips	Triticale
Winter/ spring peas	Winter rye
	Winter wheat

Table 2.2. Specific coefficients for the crop combinations used for Soil Carbon CareTaker model.

Variable	Crop Type					
	Corn Stubble	Alfalfa + Oats	Alfalfa+ Oats + Peas	Alfalfa + Oats+ Rye	Alfalfa	Cover Crop (Winter Rye and Hairy Vetch)
Lignin (%)	6.31	9.310	8.120	7.440	14.40	4.28
Nitrogen (%)	0.97	2.440	2.700	2.620	2.240	3.46
Harvest Efficiency	0.54	0.765	0.765	0.765	0.765	0.90
Stubble	0.31	0.085	0.085	0.085	0.085	0.85
Roots	0.15	0.750	0.100	0.100	0.150	0.15

Table 2.3 Average temperature (°C), precipitation (mm) and silt + clay (%) range for the western, central, and eastern regions of Michigan.

Region	West	Central	East
Average temperature	8.49	8.56	8.70
Average precipitation	2.36	2.30	2.61
Silt + Clay range	29-68	25-43	23-49

Table 2.4. Percent increase or decrease from the base at the Wisconsin Integrated Cropping Systems Trial (WICST) study site (Arlington, WI). *Percent of soil carbon from the last date of simulation.

Scenario	Percent change from the base case
WISCT- base	2.92*
NoTill	56
CornOnly	7
CC	105
CC NoTill	200

Table 2.5. Percent increase or decrease from the base soil carbon averages for each region in Michigan. *Percent of soil carbon from the last date simulated.

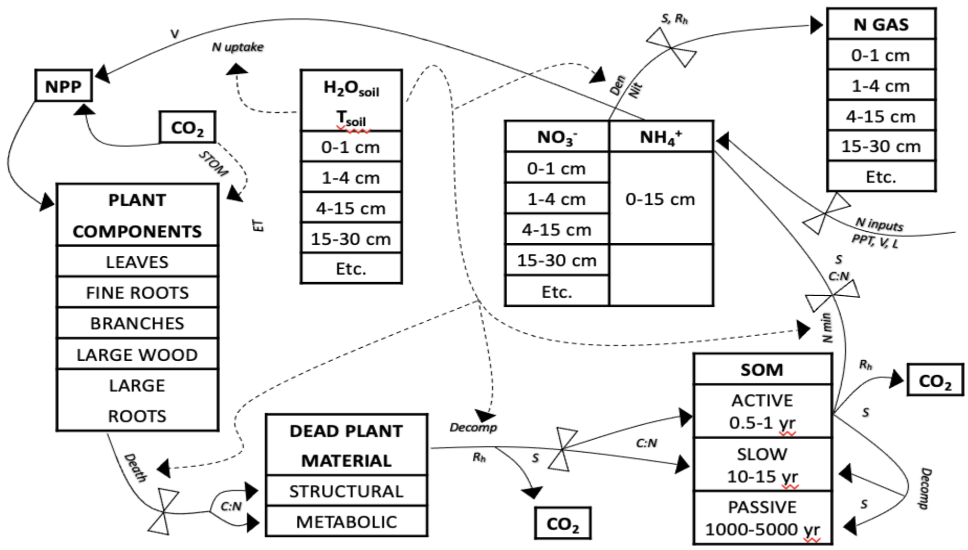
Regions	West	Central	East
Base Soil C Average (%)	83*	80*	123*
Averages of Least Change from Base Soil (%) (CornOnly)	-14	-12	-15
Averages of Greatest Change from Base Soil C (%) (CC NoTill)	350	361	278

Table 2.6. Michigan fields ranked from the least soil silt + clay percentage with the least and greatest change from the base soil carbon percentage from the last day of simulation.

Field- Soil silt + clay %	Least Change from Base (%)	Scenario	Greatest Change from Base (%)	Scenario
23	-11	CornOnly	412	CC NoTill
25	-6	CornOnly	422	CC NoTill
29	-20	CornOnly	364	CC NoTill
39	-13	CornOnly	330	CC NoTill
42	-13	CornOnly	331	CC NoTill
43	-14	CornOnly	322	CC NoTill
43	-18	CornOnly	299	CC NoTill
44	-15	CornOnly	304	CC NoTill
49	-10	CornOnly	303	CC NoTill
58	-9	CornOnly	271	CC NoTill
63	-36	CornOnly	194	CC NoTill
68	-6	CornOnly	236	CC NoTill

Table 2.7. Percent increase or decrease from the base soil total daily CO_2 loss (kg) for each scenario for the Michigan data sets used for the Soil Carbon CareTaker Model. *Percent of soil carbon loss from the last date simulated.

Scenario	Total Daily CO_2 Loss (%)
Base	12.40*
Average NoTill	-41
Average CornOnly	-40
Average CC	-42
Average CC NoTill	-34



→ = C, N flows

- - - > = Feedbacks, information flows

= Control on Process

H_2O_{soil} = Soil water content

T_{soil} = Soil temperature

S= soil texture

C:N= Carbon: Nitrogen ratio of material

V= Vegetation type

SOM= Soil Organic Matter

L= Land use

R_h= Heterotrophic respiration

N GAS= N_2O, No_x, N_2

Processes designated by *italics*

Stom= Stomatal conductance

Death= Plant component death

Decomp= Decomposition

N inputs= N Fixation, N deposition, N fertilization

Nit= Nitrification

Den= Denitrication

N min= N mineralization

ET= Evapotranspiration

Fig. 2.1. A conceptual diagram of the DAYCENT model adapted from Del Grosso et al. (2001).

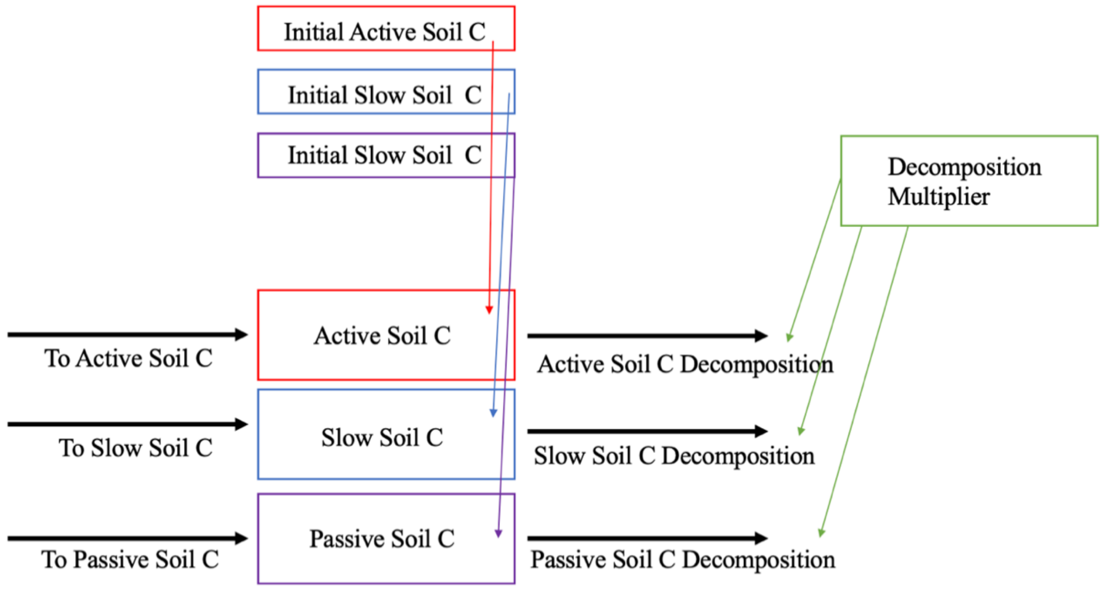


Fig. 2.2. A conceptual figure from of the initial values (kg/ha) for each soil carbon stock (rectangles) with their inflows (accumulations) and outflows (losses; black arrows; rates = kg/d). The green rectangle represents an auxiliary variable that modifies the outflow rate (kg/day) of each carbon stock.

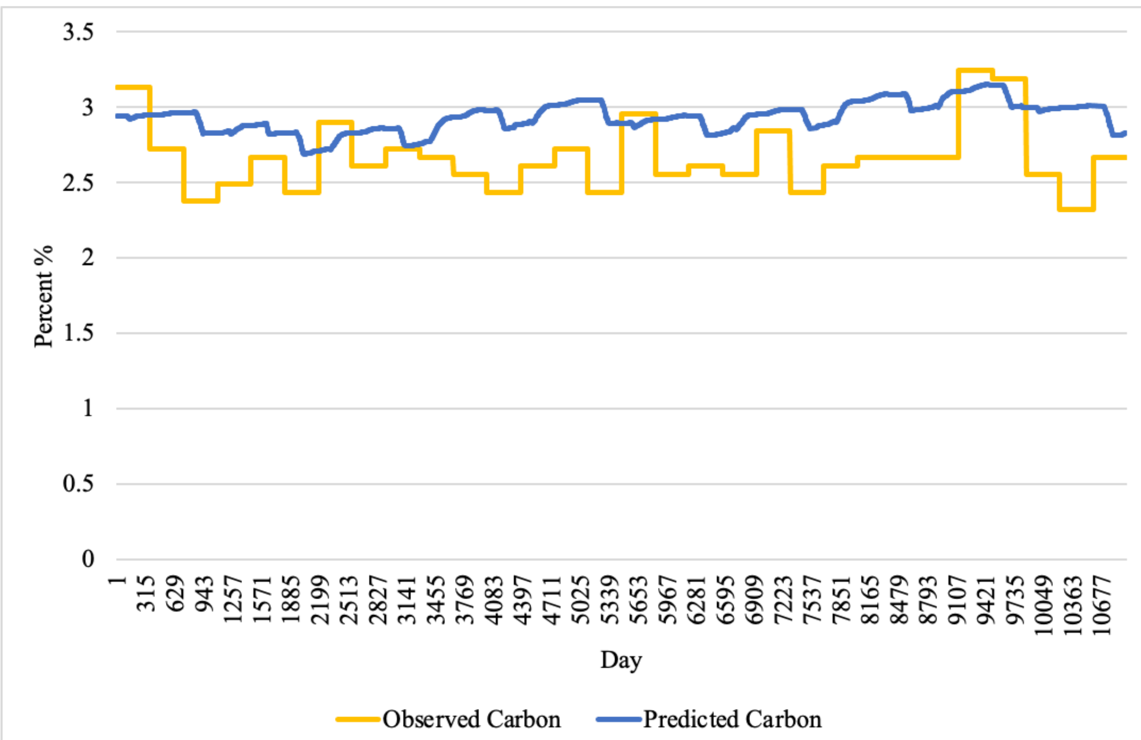


Fig. 2.3. Observed soil carbon from the Wisconsin Integrated Cropping Systems Trail plotted against predicted soil carbon from the Soil Carbon CareTaker calibration from 1989 to 2019.

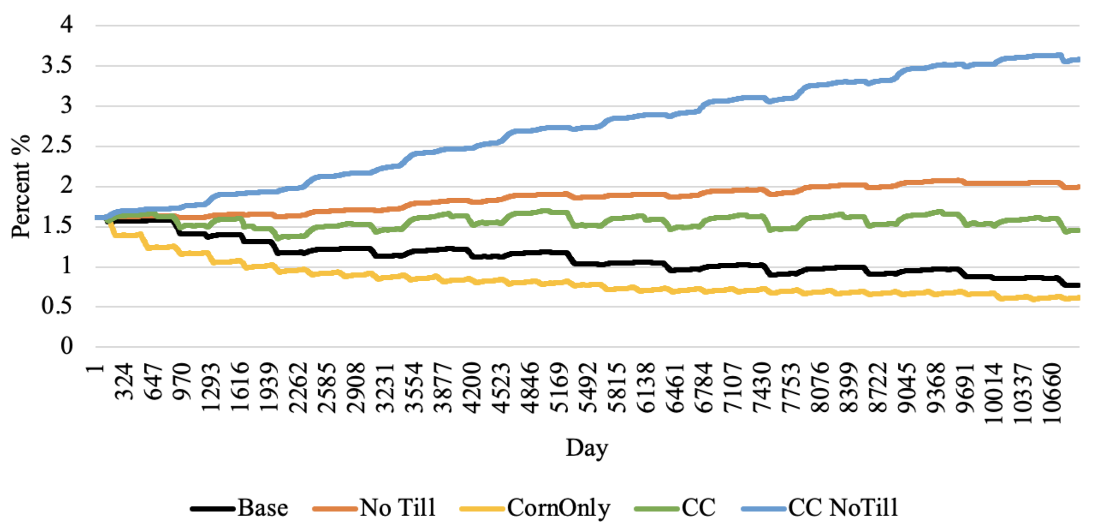


Fig. 2.4. An example of simulated soil carbon changed over a 30-year period with the different cropping scenarios; no-tillage (NoTill), continuous corn (CornOnly), addition of cover crops with tillage (CC), and cover crops with no tillage (CC NoTill) compared to the base case scenario for a Michigan dairy field.

CHAPTER 3. DEVELOPING A DRY MATTER INTAKE PREDICTION EQUATION FOR GRAZING ANIMALS BASED ON REAL-TIME ENTERIC EMISSIONS MEASUREMENTS

ABSTRACT

Cattle dry matter intake (DMI) is an essential component of calculating cattle stocking rates, determining nutrient status, and evaluating grazing efficiency. Intake of grazing animals varies on environmental factors and physiological stage of production. Cattle DMI and digestion of forages impact enteric greenhouse gas (GHG; CO_2e) emissions. Enteric emissions include methane (CH_4) and carbon dioxide (CO_2), that are produced from animals. The amount of CH_4 eructated by ruminants is affected by consumption, quality, and type of feedstuffs. Additionally, increased GHG levels indicate energy loss during the rumen fermentation process. However, there may be a silver lining to enteric GHG emissions to predict DMI of grazing animals as GHGs are highly correlated with DMI and forage nutrient composition. Currently, there is limited data on the relationship of DMI and GHG on extensive rangeland systems because it is difficult to obtain. Obtaining data for beef cattle DMI and enteric emissions on forage-based diets like extensive rangelands is needed to develop an equation capable of predicting DMI for grazing cattle. Therefore, our objectives were to: 1) measure CH_4, CO_2, oxygen (O_2) emissions and DMI of dry beef cows, and 2) use these data to develop a mathematical model capable of predicting grazing DMI. The predictive equation or precision system model (PSM) was developed using data from two feeding trials that were conducted using technology to measure enteric emissions (GreenFeed™), daily DMI (SmartFeed

Pro™), and front-end body weights (SmartScale™). This study was conducted in western South Dakota during the winter of 2022. The two feeding trials consisted of non-lactating beef cows (n = 7) receiving low (6% CP) or moderate (15% CP) quality grass hay using a 14-day adaptation period and a 14-day period of data collection. Average CH_4 (g/day), CO_2 (g/day), and O_2 (g/day) were 265 $\pm$ 8.78, 7,953 $\pm$ 228.83, 5,690 $\pm$ 1,488.19, for the low treatment and 215 $\pm$ 13.63, 6863 $\pm$ 393.79, 5,244 $\pm$ 328.32 for the moderate treatment respectively. The PSM was evaluated for accuracy [mean bias (MB)] and precision (R^2). Initial models were less than desirable for individual DMI with a range of R^2 of 0.01-0.36 for single and multiple linear regression. Using herd-level data and a 3-day smoothing the CH_4 model produced the best results with an R^2 and MB of 0.91 and -255.00, respectively. A major limitation was poor GreenFeed™ use rates resulting in a limited sample size to compare with individual daily DMI data. This pilot study provides a novel methodological approach to achieve data collection for rangeland cattle using multiple precision livestock technologies simultaneously. Advances in DMI estimates for grazing cattle will have the potential to enhance stocking rate estimates, supplementation, and individual animal efficiency, leading to lower cost, optimized resources, and enhanced environmental sustainability.

Keywords: Greenhouse Gases, Dry Matter Intake, Beef Cattle, Rangeland, Precision Technology, Enteric Emissions

INTRODUCTION

Beef Cattle Management on Rangelands

Dry matter intake (DMI; g/d) is an essential measurement for many purposes such as determining nutrient requirements, evaluating feed efficiency, and calculating stocking rates on rangelands. Dry matter intake differs for beef cattle depending on their environment and physiological stage of production (Van Soest, 1994). Cattle on rangelands are often a variety of classes and physiological stages making management difficult. Balancing these factors with seasonal changes in crude protein (CP) and precipitation is important in determining forage intake, which ultimately impacts stocking rates.

Dry matter intake on rangelands is important to determine the nutrient status of the cattle and for evaluating feed efficiency (Fox et al., 1988). Feed efficiency is the term to quantify milk/meat production from feed consumption (Korver, 1988) and it has been estimated that 5% of all dietary energy used for beef production goes toward protein deposition (Dickerson, 1978). When compared to other livestock, cattle are inefficient animals (Dickerson, 1978). Thus, it is important to evaluate feed efficiency for producers to extend pasture availability, reduce supplement costs and guide genetic selection within their herd (Dickerson, 1978; Hill, 2012). Within grazing systems harvest efficiency is used to evaluate the forage that is apparently ingested by the grazing animal from the forage that is produced and is reported as a percentage (NRHP; Butler et al., 2003). Smart et al. (2010) used three different intake equations for harvest efficiency and found significant differences in harvest efficiency by stocking rates ($P = 0.0001$). With a goal of 25% harvest efficiency, the moderate stocked pastures were closest to this target, while heavy stocked pastures were 13-16% higher and light stocked pastures were 6-10% lower (Smart et al., 2010). Although harvest efficiency gives a general view of the grazing performance of a herd as a whole, it makes it very difficult to get individual DMI. It is difficult to determine feed efficiency for individual grazing animals because we do not know their DMI. Several methods have been developed to directly measure DMI of grazing animals in pasture, but these methods are difficult, time consuming, and laborious in nature (Cottle, 2013).

Dry Matter Intake Measurement Methods for Grazing Animals

Methods such as direct observation, depletion of feed, hand-plucking, total fecal collection, and internal/external markers are used to estimate intake of forages by grazing cattle (Cottle, 2013). Direct grazing observations of domestic livestock can help ascertain what they consume, when they eat different plant species, where they are eating, and how the animal eats on rangelands but cannot establish how much they are eating, therefore is a poor indicator of DMI (Bjugstad et al., 1970). One of the most effortless techniques for estimating grazing is the depletion of a food resource, which bases intake estimations on how much herbage mass (kg/ha) is left post grazing. Since plants naturally grow and are defoliated these techniques are only good for a short time scale and therefore, at longer time scales consumption would be underestimated (Mayes and Dove, 2000). The hand-plucking method is used for forage intake estimations, diet selection and quality of diet. Hand-plucking uses a technician that watches grazing animals and picks "bite sized" grass samples to mimic the animal while it is grazing. To successfully do this measurement it needs to be done in a very low stocked pasture to guarantee that there will be similar plants to pluck next to where the animals are grazing (Cook, 1963). One limitation to this method is that it has been deemed to be unsatisfactory for mixed species pastures (Cook and Harris, 1951). Although a skilled observer could mimic bite size and grass swards with homogeneity in a pasture of a few grass species (Bonnet et al., 2011).

Total fecal collection uses fecal collection bags that are attached to the animal's body and weighed daily. Conventional hand feeding is the typical method to determine intake of the animal. A study found that intake estimated from total fecal output with *in vivo* digestibility was closer to actual intake (Schneider and Flatt, 1975). However, *in vivo* has some limitations because retention time for forage is not always equal (Holechek et al., 1986). Other methods to measure DMI are internal and external markers which overcomes the limitations of total grab and pull measurements and total fecal collection. Differences exist between internal and external markers and the materials of which they are composed. For example, Velásquez et al. (2021) used 12 bulls split into groups and fed four different diets at *ad libitum* for 38 days. The results indicated that chromium (III) oxide + indigestible neutral detergent fibers and chromium (III) oxide + indigestible acid detergent fiber was more precise at estimating dry matter demand, fecal output, and DMI when compared to total-tract apparent digestibility, real fecal output, and real DMI. A major limitation in this study and others is that marker recovery may be poor, therefore it is important to do a total fecal collection from at least one animal to make accurate adjustments (Velásquez et al., 2021). The equation employed in fecal marker studies is well known (equation 1):

$$(1) \quad \mathrm{I} = \mathrm{F}/(1 - \mathrm{D})$$

Where, I is intake (g/d), D is digestibility (dmnl), and F is fecal output (g/d). Although with this equation many errors occur when collecting fecal output and digestibility (Cottle, 2013).

A growing environmental concern related to grazing cattle DMI is enteric emissions, making estimating DMI an even more important factor (FAO, 2020). Beef and dairy cattle consuming forage have been reported to have up to 6% variability in methane (CH_4) production (Johnson and Johnson, 1995). Two primary mechanisms that are accounted for are 1) the amount of carbohydrates that are fermented in the reticulorumen and 2) the available hydrogen and subsequent CH_4 production based on the volatile fatty acid (VFA) ratios. Feed intake, carbohydrate type, forage processing, lipid addition, and the microflora influences CH_4 production. Increase in forage intake will subsequently increase energy loss of about 1.6%; highly digestible diets will have a decrease in CH_4 losses (Johnson et al., 1993). However, highly digestible carbohydrates fed at limited amounts can cause high CH_4 losses (Johnson et al., 1993). Soluble carbohydrate fermentation is less methanogenic than cell wall carbohydrates (Moe & Tyrrell, 1979).

Research on beef cattle has shown that non-cell wall components contribute to less CH_4 production compared to forages that have more cell wall components (Johnson and Johnson, 1995); this is because they are separated into soluble sugars which creates more CH_4 than starchy material. Further, differences in CH_4 production are caused by additional fiber substrates available for microbial fermentation (i.e., low-quality forage), resulting in methanogenesis. A relationship exists between decreased concentrates or increased forage and increased CH_4 production. Methane has also been shown to be positively correlated with body weight (BW; $P < 0.001$; Yan et al., 2009). This is due to a smaller animal ingestion of less feed, so in turn, they proportionally emit less CH_4 (Hristov et al., 2019). For example, animals such as sheep and goats have smaller rumens, so not only will they consume less forage, but they also have a shorter mean retention time that reduces CH_4 production, but they produce higher amounts of CO_2 per kg BW (Zervas and Tsiplakou, 2012).

A study by van Lingen et al. (2019) used an intercontinental database to create a prediction model for enteric CH_4 production of beef cattle using data from Europe, North America, Brazil, Australia, and South Korea. They found that DMI was the most important factor to predict CH_4 production, especially with the groups of all data combined, high-forage diets, and lower-forage diets (van Lingen et al., 2019). They found that non-linear models (Mills et al., 2003 and Patra, 2017) did not perform better than linear models (Charmley et al., 2016) with DMI as the independent variable. Patra (2017) showed better accuracy and precision for CH_4 prediction but not with the database used within this study. However, the Charmley (2016) model was developed using beef diet data with > 70% forage concentration (tropical and temperate).

Empirical modeling and mechanistic modeling have indicated that the DMI/BW ratio is important for CH_4 yields (Sauvant and Nozière, 2016). Thus, increased enteric emissions data of grazing cattle provides an opportunity to explore the correlation with DMI using mathematical models. Although field-based studies have laid the groundwork for estimating DMI, they are tedious and time consuming compared to the use of models. Nutrition models help researchers reduce costs and time when predicting DMI (NASEM, 2016; Tedeschi & Fox, 2020). For example, empirical equations such as using neutral detergent fiber (NDF) to predict DMI (Tedeschi and Fox, 2018) are tools that may give

DMI modeling reliability under similar environmental conditions (Tedeschi et al., 2019). As the quality and quantity of animal data continues to improve, the reliability of DMI models will likely increase. A major proponent of enhanced data collection for grazing livestock is precision livestock technology (PLT) (Menendez et al., 2023) and includes the ability to collect CH_4 data of grazing livestock to enhance DMI models.

The Role of Precision Livestock Technologies (PLT)

Utilizing PLT we can fill the gaps in research that have been infeasible in the past, because we can now collect high resolution data that was unattainable before (Menendez et al., 2022). One important technology affecting rangeland research capabilities is the GreenFeed™ pasture system because it can be deployed on extensive rangelands (Manafizar et al., 2017). The GreenFeed™ pasture system is a portable machine that can measure enteric emissions, specifically CH_4, CO_2, and O_2 (Fig. 1). When compared with the SF_6 and chamber methods for enteric emission measurements, the GreenFeed™ system has been shown to reliably and accurately measure CH_4, CO_2, O_2 from beef and dairy cattle in a pasture setting (Manafiazar et al., 2017; Alemu et al., 2017; McGinn et al., 2021; Ridoutt et al., 2022). Therefore, it may be possible to use precision livestock measurement tools, like the GreenFeed™, to estimate DMI in real-time, since CH_4 and DMI are highly correlated and the GreenFeed™ provides a reliable method to measure enteric emissions of grazing cattle which was not possible until recently. Thus, the objectives of this study were to: 1) measure CH_4, CO_2, O_2, emissions and DMI of dry beef cows and 2) use these data to develop a mathematical model capable of predicting grazing DMI.

MATERIALS AND METHODS

Study Area

This study took place in western South Dakota at the South Dakota State University (SDSU) Cottonwood Field Station (43º, 57’ 38.37753”, - 101° 51' 30.44387") from January until May of 2022. The average temperature for the study period was 2.4ºC (Weather U.S., 2022). Average annual precipitation is 432 mm. This area of western South Dakota is typically dominated by cool-season mid-grasses like western wheatgrass (*Pascopyrum smithii*) and warm-season short-grasses such as blue grama (*Bouteloua dactyloides*) and buffalograss (*Bochloe dactyloides*) (Dunn et al., 2010).

IACUC Statement

The SDSU Institutional Animal Care and Use Committee (IACUC) approved all procedures involving animals (approval number #A3958-01).

Experimental Design

Dry beef cows (n = 7, mean BW = 622 ± 11.79) were kept in a drylot setting. Non-lactating/non- pregnant cows with a constant nutritional demand were used to reduce the variation of energy and protein requirements for this experiment compared to pregnant or lactating cows. Cows were fed two different forage-based diets *ad libitum* to mimic a rangeland setting. The two feed treatments were grass hay 1 (G1) and grass hay 2 (G2) which represented moderate and low forage nutrient composition. Each treatment consisted of a two-week adaptation phase and a two-week collection phase (Fig. 2).

Daily samples were collected for each feeding period, dried, and weighed to determine dry matter percentage (n = 22). At the end of each two-week period, the forage was mixed into composite samples (n = 4), which were sent to Servitech Labs (Hastings, NE) for testing in triplicate (n = 12). Forage nutrient analysis for each grass hay in each phase were tested for dry matter (DM%), crude protein (CP%), and acid detergent fiber (ADF%). These measurements were used to estimate total digestible nutrients (TDN%). During the collection period for G1 and G2 we collected individual enteric emissions (g/hd/d), individual daily DMI (kg/hd/d), and individual daily cow weights (kg/hd/d).

Precision Technologies

To collect these measurements, we used three precision measurement technologies: the SmartFeeder™, GreenFeed™, and SmartScale™ (C-Lock Inc., Rapid City, SD). All devices followed suggested experimental protocols (i.e., weight and gas calibrations) to ensure data quality throughout the experiment (C-Lock Inc., 2022). The SmartFeeder™ was used to collect daily individual intake by measuring disappearance (Fig. 3). To do this, the device takes the total feed in the bin (kg) minus the disappearance (kg) per each feeding event (C-Lock Inc., 2021), which resulted in intake values on an as-fed basis per cow (kg/h/d). Later intake was converted to DMI using percent dry matter values.

The GreenFeed™ (Fig. 4) was used to measure CH_4, CO_2, and O_2 emissions (g/hd) from the cows on an individual basis in real-time. The GreenFeed™ uses radio frequency identification (RFID) tags that are unique to each animal. The cattle were baited into the head box of the GreenFeed™ using an alfalfa (*Medicago sativa*) pellet (CP = 15%, ADF = 38%, and NDF = 48%). Alfalfa pellets were selected to align with the forage-based treatments. The GreenFeed™ fed cattle at a rate of ~35 g every 30 s with eight drops for each feeding period. Each individual cow had a max of five feeding periods per day: a 1.4% maximum potential contribution of CP to basal diet in the current study. When an animal is consuming the pellets distributed by the GreenFeed™ system (≥ 2 minutes required), the system measures airflow rate, background CH_4 and CO_2 concentration so it can measure gas (CH_4 and CO_2) fluxes from the animal. The non-dispersive infrared analyzer, and head proximity sensor then filter out samples where the head is not in optimal position to give satisfactory measurements (Manafiazar et al., 2017).

Other studies have tested the GreenFeed™ in an open environment and within a respiratory chamber (RC) to assess differences in background gas concentration (McGinn et al., 2021). This procedure was designed to mimic the background gases of animals on range (outdoor environment; low background gas) and those in a barn (indoor environment; high background gas). There was a small but significant difference between the GreenFeed™ and the RC for CH_4 measurements (McGinn et al., 2021). However, they found no difference with the GreenFeed™ and mass flow controller outside the chamber ($P > 0.726$). For CO_2 emissions there again was a significant difference ($P < 0.013$ and $P < 0.007$). All changes were less than 3% and therefore indicated that the GreenFeed™ is a reliable system to accurately measure CH_4 and CO_2 in both a range and confined (e.g., barn) setting (McGinn et al., 2021). In our study, the results from the GreenFeed™ units were consistent despite extremes in weather conditions and temperature ranges, further indicating that readings are reliable. It is likely that the GreenFeed's ™ ability to collect enteric emissions data likely surpasses that of the RC and is therefore an adequate substitute for collecting CH_4, CO_2 and O_2 on rangelands.

The Smartscale™ (Fig. 5) was used to measure individual front-end weights that were then converted to full BW ($R^2 = 0.92$; Brennan et al., 2023), using independent full

BW that were taken using a conventional scale collected at the beginning and end of each phase (n = 35). The chute weights were collected using a hydraulic squeeze chute (Silencer™, Stapleton, NE). on load cells and bars (Tru-Test, Mineral Wells, TX).

Data Pipeline

For all three precision technologies, RFID tags were used so that data collected could be paired with individual animals, and we later combine all three data sets into one data pipeline. Data were sent to the cloud remotely and downloaded either through a direct download or application programming interface (API) from the C-Lock, Inc. web interface and put into Program R. Automatic data collection from multiple precision technologies resulted in a large amount of data that needed to be cleaned and processed into a usable format.

To process the data and conduct a statistical analysis we integrated these three precision data streams into Program R for Statistical Computing (Team R, 2019; R Studio version 1.4.1717). Using R Studio we ran descriptive statistics, removed outliers, and checked for normality, homoscedasticity, and independence. After data met these conditions, a mixed model analysis of variance (ANOVA) (*lme4* package, $P < 0.05$) (Bates et al., 2015) was run for each gas emission (CH_4, CO_2, and O_2) and DMI to determine differences between each treatment (G1 and G2; $P < 0.05$). We used a mixed model ANOVA instead of a one-way ANOVA because of lack of independence between variables; treatment was the main effect and animal was the random effect.

Comparing Contemporary Models

We compared the observed DMI data set with the two most used DMI equations for beef cattle requirements, the first being NASEM (2016) using metabolic BW and net energy for maintenance shown in equations 2 and 3:

$$(2)\mathrm{NE_m\ Intake} = \mathrm{BW}^{0.75}\ \mathrm{x}\ (0.04997\ \mathrm{x}\ \mathrm{NE_m}^2 + 0.04631$$

Where, NE_m Intake is net energy for maintenance intake (Mcal/d), $BW^{0.75}$ is metabolic BW (kg), and NE_m is net energy for maintenance (Mcal) required by the animal.

$$(3)\ \mathrm{DMI} = \frac{\mathrm{Total\ NE_m\ Intake}}{\mathrm{Dietary\ NE_m\ Concentration}}$$

Where DMI is dry matter intake (kg), Total NE_m intake is the amount of energy that was consumed by the animal and the Dietary NE_m Concentration is the concentration of energy in the feed/forage consumed (Mcal/day).

The second equation is used primarily for calculating rangeland stocking rates (AUM/ha) and is based off DMI as a percentage of BW (equation 4):

$$(4)\ \mathrm{DMI} = \mathrm{BW\ X}\ (1.8\%/100)$$

Where, DMI is dry matter intake (kg/d), and BW is cow body weight (kg) multiplied by 1.8%. This percentage was used because a non-lactating cow is assumed to consume 1.8% of their BW (Lalman, 2004).

In phase two we evaluated the prediction of the NASEM and percent BW DMI equations against observed DMI, using the Model Evaluation System (MES; Tedeschi, 2006) for precision (R^2) and accuracy (mean bias; MB). The coefficient of determination (R^2) measures the quantity of variance connecting the observed and predicted values, with values closer to 1 being more precise (Menendez et al., 2020; Kvålseth, 1985). The

MB specifies the differentiation of means between the observed and predicted values (values closer to 0 being better) (Bandemer, 1978).

Predictive DMI Model Development

Raw data for each model was brought into Program R or Vensim DSS™ (a visually based modeling software) and outliers were removed using a 1.8%-3.0% BW rule. An interquartile range was used to remove DMI and BW outliers. We found the lower bounds of the quartile by calculating Q1 -1.8% * interquartile range and the upper by Q3 + 3.0% * interquartile range. We used 1.8 to 3.0% BW because it is the common range for minimum and maximum fill of the gastrointestinal tract of a grazing animal (Van Soest, 1994).

After processing the data, we utilized a linear regression and multiple linear regression approach to predict DMI from enteric emissions and BW. First, we regressed DMI by CH_4, CO_2, O_2, and BW for each treatment (G1, G2). Then we regressed the same individual covariates against DMI using all data (i.e., combination of treatments G1 and G2). For the multiple linear regression, DMI was regressed against a combination of all covariates both by treatment and combination of treatment data.

Meta-modeling is the use of models to inform models (Tedeschi and Fox, 2020). We used this approach and combined all cow data (n = 7) for DMI and each gas to obtain a herd average for DMI and gases. Next, data was smoothed using a 3-day smoothing function in order to account for delayed effects from previous rumen fill on DMI for subsequent days. These modeled data were then used to re-analyze the same linear and multiple linear regression models as mentioned previously for G1 and G2 datasets.

RESULTS

The results of the nutrient analysis indicated that the nutrient composition of G1 forage had a higher CP and TDN and lower ADF compared to the G2 diet. The CP and TDN for G1 were higher by 59.71% and 14.08%, respectively. However, the ADF for G2 was greater by 12.64% (Table 1). Dry matter intake and emissions data showed that G2 had higher average DMI, CH_4, CO_2, and O_2 by 18.43%, 22.68%, 15.88%, and 8.52%, respectively ($P < 0.05$; Fig. 6-8). Ranges for each gas per treatment showed that G2 had a greater range for CH_4 and O_2, while G1 had a greater range for CO_2 (Table 2). However, O_2 was not significantly different between treatments ($P > 0.05$). When we evaluated observed DMI data with the NE_m Intake and the DMI using the %BW equation, we found that both NASEM and %BW underpredicted DMI, until data from both treatment groups were combined (Table 3). After the combination of both grass hay treatments the NE_m Intake DMI equation achieved the highest level of precision and accuracy.

Using linear regression, the most precise was DMI by CH_4 for the G1 treatment compared to all other covariates and treatment combinations ($R^2 = 0.36$). The highest R^2 value for DMI by CO_2 was for the G1 treatment with a R^2 of 0.21, but with no significant correlation ($P > 0.05$). Using combined treatment data (G1 and G2), the highest R^2 value was 0.25 for DMI by CH_4. Linear regression results were determined to be unsatisfactory for our purposes of predicting DMI.

Evaluation of DMI using multiple linear regression for all gases (CH_4, CO_2, and O_2) was most precise for the G1 treatment data (Table 4). Inclusion of BW as a covariate increased the R^2 for G1, G2, and the combination of treatments (i.e., G1 combined with G2) by 35%, 97%, 63% respectively, which was only slightly less precise than simple linear regression using BW alone (Table 5). Re-evaluation of the simple and linear regressions between CH_4, CO_2, and O_2 to explain DMI using the smooth data for both DMI and gases at a herd-level average resulted in a strong relationship between each gas in the combined treatments with a range of R^2 values from 0.85 to 0.91 (Table 6). This resulted in the development of a DMI equation based on enteric emissions that achieved a reliable DMI estimation for grazing dry beef cows, at a herd level.

DISCUSSION

We were successful at deploying three PLTs to collect and process individual animal DMI, enteric emissions, and weight data. These PLTs enabled us to determine differences between G1 and G2 treatments and use these data to develop a model capable of predicting individual DMI.

Considerations of PLT Data and Methods

Conducting an experiment using PLTs requires the ability to clean and organize data into a consistent format, a major barrier to effective precision technology implementation (Menendez et al., 2022). This data barrier is substantially increased when multiple PLTs are utilized. In the current study, a data pipeline was successfully developed to integrate data from the SmartFeeder™, GreenFeed™, and SmartScale™ technology. One key challenge in the current study was finding a unique attribute to organize these multiple data sets. We overcame this issue by creating a separate "ID" column to merge by date and RFID. Once large amounts of data are collected and organized into a single data frame there may be missing data from certain times/dates. Missing data occurs when animals don't use the technology or when communication or hardware/software errors occur. Thus, when using PLTs users should plan on having a larger sample size than required and understand the PLT strengths and weaknesses to limit missing data (Jacobs et al., 2022). Open-source data pipelines for specific single or multiple PLT help expedite future researchers' ability to clean and combine data when using similar technologies (Brennan et al., 2023). This is critical since programs like Excel simply are not sufficient to handle the amount of data generated by PLTs. Another major limitation of precision data is the utility in mathematical models because models require consistent datasets and, unless an automatic interpolation is incorporated, they cannot produce reliable results (Jacobs et al., 2022; Tedeschi, 2019). A critical next step for precision livestock research is to further enhance the pipeline developed in the current study and include open-source code examples and tutorials to accelerate PLT research and broader applications as PLT technology use increases (Brennan et al., 2023).

Technology Challenges

Deploying precision technology provides new means for experimentation, data collection, and model development. As expected, several challenges occurred for each technology. The SmartFeeder™ was not created to be used with chopped hay, requiring us to clean out the head gate to prevent it from getting jammed. Wind also played a factor because it can blow forage out of the tub; although, it is accounted for on the C-Lock web interface as being categorized as an "Unknown" disappearance. Lastly, correct tub height is a crucial factor. If the tubs are too tall, cows will not be able to utilize the full amount of feed provided and will have to be fed more frequently. If they are too low, then the cows are able to be more selective and can pull out feed or push feed over the lip of the tub, potentially biasing DMI data. Further, training cattle to use the GreenFeed™ is difficult and they need adequate time to adjust to this machinery. Baiting animals with a more palatable feed is a good way to get them close enough to interact with the GreenFeed™. As previously mentioned, not all cows will use the GreenFeed™, so having an initially large sample size is important for achieving adequate samples after culling non-adopters, something not accounted for in a statistical power test. The SmartScale™ had no significant limitations.

In the current study, the individual DMI data for G1 and G2 treatments were found to be reliable being between the range of 10.22-20.52 kg for cows' weighing 509-783 kg. On average cattle in our study consumed 2.3% BW, consistent with another study that reported similar DMI ranges (2.2-2.9% BW) for dry beef Angus cows (535-564 kg BW) (Wagner et al., 1986). As more individual cow DMI data becomes available, there may be a potential to assess DMI more closely relative to weight, body condition score, production stage, genetics, and individual efficiency.

In terms of enteric emissions, we found comparable emission levels with other studies on beef cows. Our average CH_4 was 243 g/d and ranged 129-342 g/d for G1 and G2 (Table 2). Whereas McGinn et al. (2021) reported an average of 309 g/d and Guyader et al., (2015) reported a range of 143-372 g/d (Guyader et al., 2015; McGinn et al., 2021). Our average was 7,490 g/d for CO_2 emissions and ranged from 2,951-9,827 g/d (Table 2), comparable to the reported average CO_2 of 8,223 g/d by McGinn et al. (2021). Oxygen emissions from G1 and G2 in the current study were an average of 5,500 g/d and ranged from 2,149- 7,531 g/d (Table 2). Previous numbers have been reported, but these O_2 averages were 7,922 (g/d); 30% higher than those we collected (Aubry and Yan, 2015). Comparable enteric emissions results are important because it indicated the GreenFeed™

measurements in the current study were appropriate for developing an enteric based DMI model.

The current study was limited with a low and inconsistent GreenFeed™ sample size, which likely reduced correlations between observed DMI and enteric emissions measurements. The GreenFeed™ emissions monitoring system was used to determine the repeatability of CH_4 and CO_2 emissions using 28 beef heifers in a drylot pen for 59 days (Manafiazar et al., 2017). Overall, they found over a 7 or 14-day sampling period that the GreenFeed™ system produced measurements with low variability in gas emissions and yield (gas/standardized DMI). Additionally, a high repeatability and correlation with gases and feed intake (CH_4 = 0.50 and CO_2 = 0.62) were determined; however, 1 or 3-day samples resulted in larger variability with emissions and low correlation with DMI (Manafiazar et al., 2017). Thus, animals who do not visit the GreenFeed™ often can produce large errors within the averages of samples. Manafiazar et al. (2017) noted that there is potential for the GreenFeed™ system to represent animal CH_4 and CO_2 emissions and yield with a 7 to 14-day sampling period and 20 or more samples per animal. Although this helps determine general herd level CH_4 estimates, it fails to account for individual enteric emissions and diurnal variations.

For example, using 14-day derived values for beef cows will result in an over or under estimation when multiplied by number of animals in the herd. This is because individual changes in enteric emissions production rates (e.g., g CH_4 per hour) change relative to rumen fill and nutrient composition of the digesta (Tedeschi and Fox, 2020). Further, our study demonstrated the need to assess sub-daily and seasonal variation of forage quality as the quantity and quality of GreenFeed™ data improves for individual animals in rangeland settings. Other methods exist to collect enteric emissions data such as a portable laser methane detector (LMD). The LMD needs to be within 1-3 m and can be influenced by background CH_4 and environmental factors such as wind. Recordings for the LMD need to be 3-5 minutes long for accurate readings (Sorg, 2021). Using this technique is difficult for grazing animals because you need to be close enough to the animals and have them remain still for a period of time (Roessler and Schlecht, 2021). The majority of LMD studies have occurred in milking parlors, tie stalls (Denninger et al., 2020) individual pens (Rooke et al., 2013), and weighing facilities (Reintke et al., 2020). Consequently, results of these studies are difficult to weigh against our study that was conducted in a rangeland setting.

Evaluated Differences in Treatment

We identified significant differences in DMI, CH_4, and CO_2 between the treatments G1 and G2. However, we were surprised with the differences in DMI results for G1 and G2. We expected that the G1 treatment would have consumed more than the G2 treatment due to higher CP and TDN levels. It is possible that the hay processing methods impacted daily consumption rates. For example, the moderate treatment (G1) was flaked hay pulled from large square bales while G2 was chopped hay; cattle preferred the latter. Hay availability and processing was limited due to persistent drought in 2021 prior to the study, hindering our ability to secure different hay qualities that were processed similarly. Thus, an opportunity to improve this study in the future is to have consistent hay sources and processing, and with a broader range of nutrients. For example, securing hay from the same field at different dates would provide the desired treatments and reflect CP variation of forages throughout the growing season, allowing the study to capture a potentially wider response in enteric emissions. However, the differences in enteric emissions we found were consistent with the known relationship of high fiber (G2) having increased emissions compared to lower fiber (G1) content (Johnson and Johnson, 1995).

Modeling

Many models have been developed for DMI for beef cattle (Smith et al., 2021; Cottle, 2013; Galyean and Gunter, 2016) however, it is critical to keep the development of new models as simple as possible (Sterman, 2000; Tedeschi and Fox, 2020; Menendez et al., 2020). Given the size of our data set and the models' purpose our use of regression modeling was the appropriate first step compared to more advanced artificial intelligence (AI) modeling approaches (Jacobs et al., 2022).

Single and Multilinear Regression

Linear regression was not satisfactory to estimate DMI using the available dataset. Although it was unsatisfactory for our study, previous research has shown a strong correlation between DMI and enteric emissions. Satisfactory levels have been 0.63 R^2 (Ellis et al., 2007). Further, another study reported that predictive performances can often be a neglected theory when assuming that machine learning (ML) algorithms are the only or supreme modeling technique (Franco et al., 2023). Although we found favorable levels of precision for combined data, there were significant data gaps, potentially biasing our regression statistics with high and low anchor points (Fig. 9). Thus, additional data collection will provide more robust data in order to resolve this potential bias. Further, the current study helps to facilitate future data collection as it identified (e.g., poor GreenFeed™ adoption rates).

The most precise modeling results were achieved when we re-ran our regressions with our original raw data on a herd average and applied the 3-d smoothing instead of a daily DMI. Though, manipulation of the data should be done with caution to avoid false levels of model confidence and adequacy of predictions. The purpose of this pilot study was to create a base model and identify important factors that needed to be accounted for, in this case the effect of previous DMI, on rumen kinetics and enteric emissions. Thus, we were successful in creating a model capable of predicting DMI that demonstrated the fundamental relationship between enteric emissions and DMI. Although additional data is essential to more rigorously evaluate the relationships between individual cow DMI and forage quality levels.

Incorporating Body Weight

Body weight can give producers a rough estimate of how much their cattle may be consuming on rangeland, but as our study showed, the %BW DMI equation underestimated intake. This underestimation can be due to the exclusion of key factors such as rumen fill, forage quality, or metabolic requirements when BW alone is used (Koch et al., 1963.; Van Soest, 1994). Other studies have used the forage net energy equation that incorporates individual shrunk BW and standing forage NE_m concentration (Undi et al., 2008). In study conducted by Undi et al. (2008) standing forage was estimated using the hand plucked samples to mimic the forage that would be consumed by animals. Undi et al. (2008) also used the Minson equations which employs BW and ADG of individual animals (Minson and McDonald, 1987). It was determined that the forage net energy equation had a DMI range of 0.6- 4.7% and the Minson equation predicted an intake of 0.9-2.2% with an average of 1.7% and 2.3%, respectively.

Although the DMI values are different, the Minson equation that used BW was the least variable when compared to other DMI predictions used in the study (Undi et al., 2008). Overall, BW equations are uncomplicated, but they do not consider the outstanding factors that may affect intake (NRC, 2016) which provided the opportunity for the current study to use precision livestock technology.

The current study results set a baseline for rangeland cattle and highlight the need for further research into other animal classes regarding enteric emissions and DMI. Further data for the different phases is critical since the dry phase is relatively short (< 3 months) compared to the pregnant or lactating phases which combined represent > 15 months. Therefore, future studies may incorporate different animal classes that provide varying degrees of emissions and DMI.

CONCLUSION

This pilot study was successful in developing a sound methodological approach to more adequately address PLT research and modeling of DMI using the GreenFeed™ pasture device. Going forward, the development of a data pipeline for the integration of multiple PLTs is likely to advance investigation into DMI prediction and other studies of interest. Unintended advantages of this study were the collection of enteric emissions for dry beef cows in a forage-based setting, which has not previously been collected. This is important as cattle represent 65% of the livestock sector GHG emissions and beef production and dairy products are responsible for 41% GHG emissions (FOA, 2022). With improved understanding of the impact DMI has on GHG from beef cattle, we can facilitate further discussions about ways that GHG can be mitigated from the cow-calf sector. For example, DMI estimates using PLT have the potential to decrease overgrazing of rangeland by 458,812 ha in South Dakota alone (Menendez et al., 2023). Thus, using the GreenFeed™ systems to improve DMI estimates, and consequently stocking rates, is an important tool for achieving sustainable agriculture in terms of climate change and production efficiency as rangelands and pasturelands comprise 311 million ha and 53 million ha, respectively, in the United States and are a key economic driver (Menendez et al., 2022).

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TABLES AND FIGURES

Table 3.1. Nutrient analysis results from moderate (G1) and low (G2) forage treatments. The feed was tested for dry matter (%DM), crude protein (%CP), acid detergent fiber (%ADF), which were all then used to calculate total digestible nutrients (%TDN).

Feed Treatment	%DM	%CP	%ADF	%TDN
G1	93.3	13.9	38.7	55.4
G2	93.4	5.6	44.3	47.6

Table 3.2. Dry matter intake (DMI), methane (CH_4), carbon dioxide (CO_2), and oxygen (O_2) enteric emissions (kg) averages (AVG) and ranges (RG) for each treatment (moderate-quality grass hay 1 = G1 and low-quality grass hay 2 = G2) and combined treatment data.

DMI and Gases (kg)	n	G1	n	G2	Combined
AVG DMI	17	13$\pm$0.48	23	16$\pm$0.50	15.49$\pm$0.40
AVH CH_4	17	215$\pm$13.65	23	265$\pm$8.78	243.83$\pm$8.57
RG of CH_4	-	129-323	-	191- 342	129.33-342
AVG CO_2	17	6,863$\pm$393	23	7,953$\pm$228	7,490.02$\pm$226
RG of CO_2	-	3,952-9822	-	5,923-9827	3,951.84-9827
AVG O_2	17	5,244$\pm$328	23	5,690$\pm$148	5,500$\pm$164
RG of O_2	-	2,149-7532	-	4,348-7046	2,149-7531

Table 3.3. Predicted dry matter intake (DMI) using NASEM (2016) and 1.8% body weight (BW) equations for moderate-quality grass hay (G1), low-quality grass hay (G2), and combined treatments. Using the levels of precision (R^2) and accuracy [mean bias (MB%)].

Model to predict DMI	R^2	MB %
G1: NASEM	0.07	0.06
G1: BW	0.07	2.71
G2: NASEM	0.06	5.05
G2: BW	0.59	5.32
Combined: NASEM	0.35	2.65
Combined: BW	0.15	3.91

Table 3.4. Levels of precision (R^2) determined by linear regression of dry matter intake (DMI) for moderate-quality grass hay (G1) and low-quality grass hay (G2), and treatments combined (G1 & G2) against methane (CH_4), carbon dioxide (CO_2), and oxygen (O_2).

	R^2 Value		
Treatment	CH_4	CO_2	O_2
G1	0.36	0.09	0.02
G2	< 0.01	0.02	-0.01
G1 & G2	0.25	0.16	0.06

Table 3.5. Linear regression for all gasses combined [methane (CH_4) carbon dioxide (CO_2) and oxygen (O_2)], combined gases and cow body weight (BW), and cow BW alone for moderate-quality grass hay (G1) and low-quality grass hay 2 (G2) and combined treatments (G1 and G2).

Model to predict dry matter intake	R^2	MB %
G1: CH_4	-0.07	-196.29
G1: CO_2	0.27	<1
G1: O_2	0.64	<1
G2: CH_4	-0.07	-254.99
G2: CO_2	0.38	<1
G2: O_2	0.38	<1
Combined: CH_4	0.91	-255.00
Combined: CO_2	0.68	<1
Combined: O_2	0.70	<1

Table 3.6. Predicted dry matter intake (DMI) using methane (CH_4), carbon dioxide (CO_2) and oxygen (O_2) for moderate-quality grass hay (G1) and low-quality grass hay (G2) and treatments combined (G1 & G2). Using the levels of precision (R^2) and accuracy [mean bias (MB%)].

	G1	G2	G1 & G2
Gases (CH_4, CO_2, O_2)	0.40	0.02	0.27
Gases + BW	0.53	0.73	0.73
BW	0.45	0.73	0.75

Fig. 3.1. Photo of GreenFeed™ pasture system 297 deployed in pasture. This system is placed on a trailer and is solar powered.

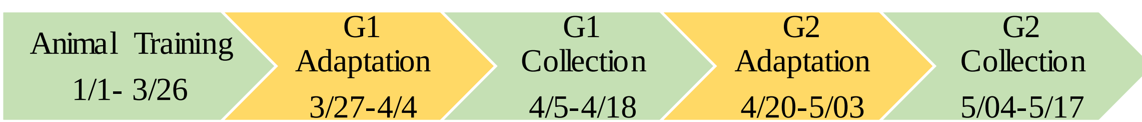

Fig. 3.2. Diagram of animal training, adaptation, and collection phase dates for moderate (G1) and low (G2) diet treatments conducted in the winter of 2022 (January through May).

Fig. 3.3. Set up of three mobile SmartFeeder™ units at the South Dakota State University Cottonwood Field Station drylot (Cottonwood, SD). Each feeder contains two precision feeding bunks.

Fig. 3.4. GreenFeed™ unit 297 deploy at the South Dakota State University Cottonwood Field Station drylot (Cottonwood, SD).

Fig. 3.5. Example of a cow using the SmartScale™ attached to the Ritchie Livestock Waterer in the drylot at the South Dakota State University Cottonwood Field Station (Cottonwood, SD).

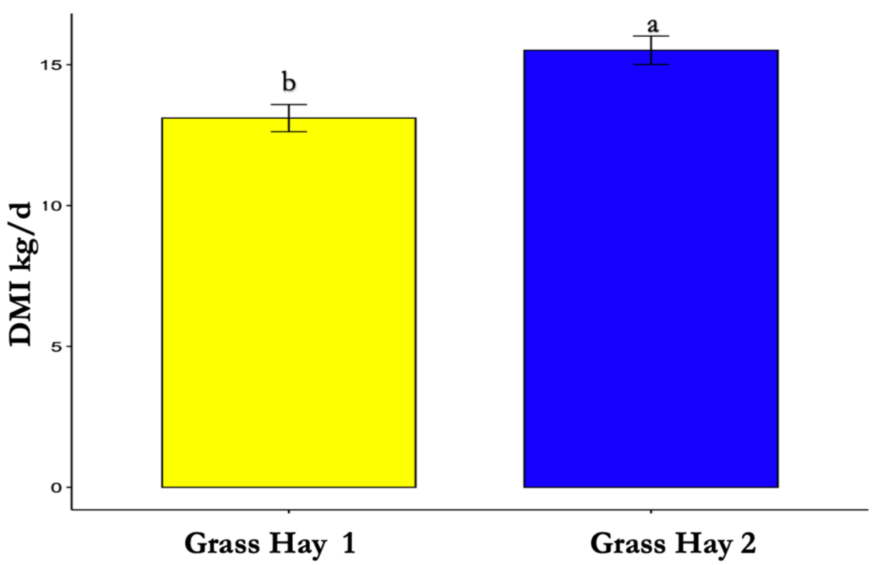

Fig. 3.6. Differences in average dry matter intake (DMI) by treatment (P < 0.05).

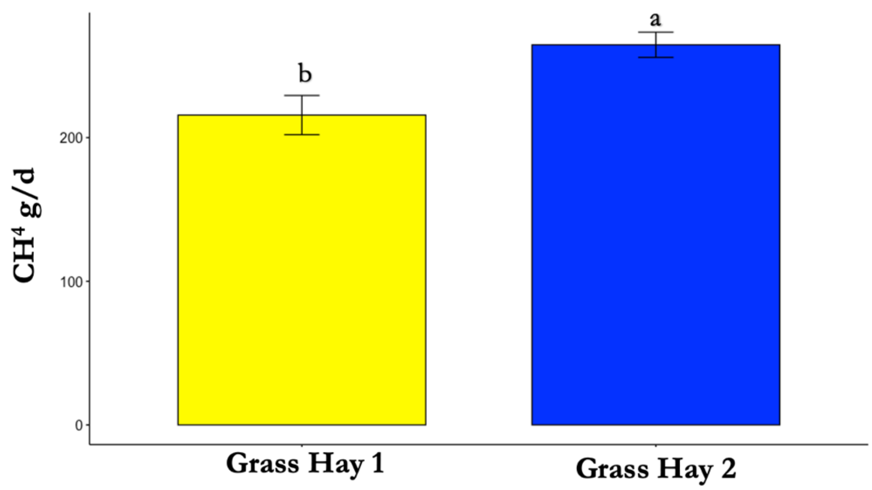

Fig. 3.7. Differences in average methane (CH_4) production by treatment ($P < 0.05$)

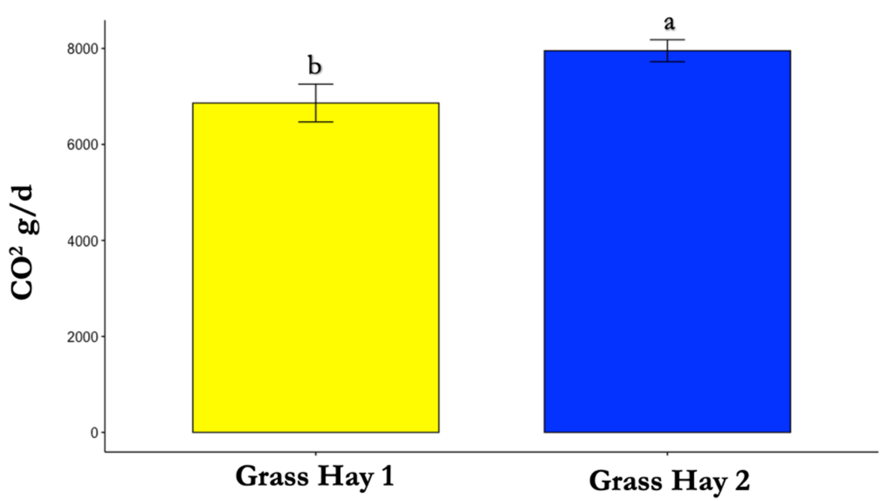

Fig. 3.8. Differences in average carbon dioxide (CO_2) production by treatment ($P < 0.05$).

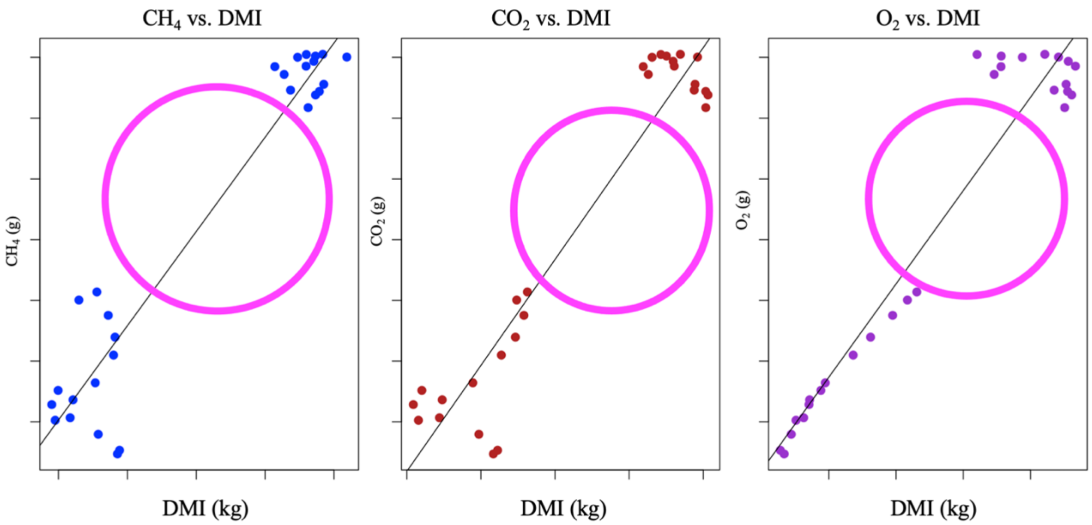

Fig. 3.9. Combined treatments, moderate-quality grass hay (G1) and low-quality grass hay (G1), and dry matter intake (DMI) graphed against methane (CH_4), carbon dioxide (CO_2) and oxygen (O_2). The pink circles represent data gaps.

CHAPTER 4. IMPLICATIONS

Soil Carbon

We were successful in developing mathematical models that encompass soil carbon dynamics for dairy systems and dry matter intake (DMI) for the rangeland beef sector, which are both highly important to United States agricultural production. The Soil CareTaker model simulates soil carbon and flux with conventional and regenerative agronomic practices. Specifically, it is a modification of the DAYCENT soil carbon model to simulate complex covers (i.e., diverse cover crop species mixes). Although our model was not precise ($R^2 = 0.07$) it was accurate [mean bias = -0.26 (MB)], so we are confident in its ability to simulate soil carbon and soil carbon fluxes under different cropping and soil management practices. We reject our null hypothesis (H_0) that the simulation of complex cover will result in no difference in total soil carbon sequestration compared to conventional practices and support our alternative hypothesis (H_1) that there is a difference in soil carbon sequestration between complex covers and conventional practices.

The purpose of the Soil Carbon CareTaker was to estimate soil organic carbon (SOC) because producers need to evaluate its potential changes from different combinations of regenerative cropping practices. For our model we targeted complex covers (cover crops and intercropping) to see how SOC would change after a 30-year simulation. With a functioning and calibrated model, we then ran four different cropping scenarios for dairy fields (n = 12) in Michigan. The four scenarios were 1) no-till (NoTill), 2) continuous corn (CornOnly), 3) cover crops with tillage (CC), and 4) cover cropping with no-till (CC NoTill). We saw the highest average increase come from CC

NoTill (316%) and lowest average increase from CornOnly (-14%). Although soil carbon models are rapidly advancing to account for more granular soil carbon dynamics, we used the simplest approach possible (i.e., the most basic form of DAYCENT), because it allowed us to achieve our model's purpose and to identify key barriers to evaluating SOC in dairy agronomic systems.

Data integration is a major barrier for continued data collection and use in dairy farm simulation modeling. Opportunities will arise to seamlessly automate data integration (e.g., producer management practices and crop residue) into models through rapid and cutting-edge data collection software (on-farm) and sensor or remote sensing technology combined with data pipelines. For example, most soil carbon models have a crop and water component that could fully or partially be replaced by inexpensive and reliable sensors. Furthermore, these sensors provide near real-time observed data instead of estimated data like soil moisture at a 15 cm depth.

Strategically replacing key model components (e.g., 300 pages of calculations to determine soil moisture) with high quality and granular data such as a near real-time soil moisture sensor will likely enhance modelers' abilities to explore soil dynamics. However, more field research is needed to increase knowledge of dynamic soil properties that will affect microbes, carbon (C) to nitrogen (N) ratio, nutrient cycling, and crop productivity, especially their interrelationship within (depth) and across (heterogeneous) fields, and over time. Overall, models like the Soil Carbon CareTaker are critical for enhancing the decision-making capabilities of dairy farmers when considering the use of regenerative farming practices to increase SOC and for maintaining environmentally sustainable production.

Range Cattle Systems

We were successful at evaluating the relationship between CH_4, CO_2, and O_2 emissions and DMI of dry beef cows using multiple PLTs. This enabled us to develop an equation/model that predicts DMI from gaseous emissions for beef cattle grazing on rangeland. We rejected our null hypothesis (H_0) that cows consuming low-quality forage will have no significant difference in enteric emission than those consuming moderate-quality forage and support our alternative hypothesis (H_1) that there is a difference.

The predictive equation or precision system model (PSM) was developed using data from two feeding trials conducted using GreenFeed™, SmartFeed Pro™, and SmartScale™ devices. The PSM was evaluated for precision (R^2) and accuracy [mean bias (MB)]. Initial models were less than desirable for individual DMI with a range of R^2 of 0.01-0.36 for single and multiple linear regression. Using herd-level data and a 3-day smoothing, the CH_4 model produced the best results with an R^2 and MB of 0.91 and -255.00, respectively. However, future studies should collect a wider range of DMI and enteric emission data to overcome any potential bias in the regression. It is worth noting that the enteric emissions data collected in this study provide more insight into the greenhouse gas impact of dry beef rangeland cattle, which is an important contribution to the fields of range and animal science, given current environmental and efficiency concerns. Although our model is capable of estimating DMI using enteric emissions data, buying a GreenFeed™ is not currently cost effective or a practical strategy for most producers; however, data collected by researchers can be used to refined DMI estimation coefficients for rangeland management.

Overall, researchers can use the methods developed from this pilot study to investigate different classes of animals and forage quality types to then in turn help clarify DMI estimation models with more comprehensive and robust data. Further, our pilot study demonstrated clear strengths and weaknesses of the GreenFeed™, SmartFeeder™, SmartScale™, and big data analytics. This led to the development of open-source code and guidelines that will likely maximize the future use of these PLTs. Further, the DMI model developed in this study is a first and critical step to improving cattle management, such as stocking rates, on extensive rangeland systems using precision livestock technology.