COVER CROPPING: SENSOR-BASED ESTIMATIONS OF BIOMASS YIELD AND NUTRIENT UPTAKE AND ITS IMPACT ON SUGARCANE PRODUCTIVITY

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COVER CROPPING: SENSOR-BASED ESTIMATIONS OF BIOMASS YIELD AND NUTRIENT UPTAKE AND ITS IMPACT ON SUGARCANE PRODUCTIVITY

A Thesis

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science

in

The School of Plant, Environmental, & Soil Sciences

by

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B.S., Universidad Mayor de San Andrés, 2015
August 2022
ACKNOWLEDGEMENTS

I would like to thank my committee members, Dr. Luciano Shiratsuchi and Dr. Lisa Fultz, for all their time and contributions to this research project. A special thanks to my major advisor, Dr. Brenda Tubana, for all the help, encouragement, and patience. She taught me how discipline, strength, and curiosity can result in a great scientist and human.

I am especially grateful to all the members of the soil fertility family who have helped me with my research endeavors and to become a better researcher and person: Jose Mite, Wooiklee Paye, Jayvee Cruz, Marilyn Dalen, Dominique Galam, Hector Mendoza, Diego Mayorga, J. Bamrungrai, Barbara Campos, Daniele Scudeletti, Elias Escobar, Alejandro Lovo, Jorge Ortega, Krizzia Guardado, Skarleth Navarro and Andrew Bratton. A special mention to Daniel Forestieri for all the guidance and friendship provided during this time.

Also, thanks to the faculty and staff from the Sugar Research Station, especially to Mr. Alphonse Coco. Likewise, my gratitude to Mr. Mike Breithaupt and Ms. Sue Chin for their help with analysis at the Soil Test and Plant Analysis Lab.

Additionally, this effort would not have been possible without the financial support of the Bolivian government, the Patrick F. Taylor Foundation, and the American Sugar Cane League.

I would like to give special thanks to my parents, Héctor Fajardo, and Magda Durán, who gave support and were part of this achievement. Also, to my friends, who make this time more enjoyable.

Finally, my honest thanks to God for giving me the strength and health to persevere through all these years.
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ABSTRACT

Sugarcane in Louisiana can be harvested for up to three years from one planting. Soil cultivation along sides of established beds is done for weed control and improve fertilizer use efficiency which increases the risk of soil degradation and yield decline. Planting cover crops (CC) is a soil conservation practice and an effective strategy to improve soil health and nutrient recycling. Limited work has been done on remote sensor-based evaluation of the potential nutrient benefits from cover crops and its effect on nutrient cycling on sugarcane systems. This study was conducted to evaluate the effect of two planting methods (broadcast and drilling) and three seeding rates (100%, 50%, and 25% of NRCS recommendation) of a mix of three legumes and two brassicas CC species and a control without CC, on sugarcane yield and quality parameters, and on soil nutrients levels. This study was also used for the acquisition of normalized difference vegetation index (NDVI), collected using GreenSeeker® and multispectral camera (MicaSense® - RedEdge-M) mounted on an unmanned aerial vehicle, to correlate with CC biomass and nutrient uptake. The NDVI readings and CC biomass clippings, using the quadrat frame method, were collected a week before CC termination. Tissue analysis was carried out by C:N dry combustion analyzer and nitric acid digestion-hydrogen peroxide for multi-element analysis. Cane yield was acquired with a chopper harvester and a dump billet wagon. Quality components were obtained by a SpectraCane® automated near infrared (NIR) analyzer for quality parameters. Soil inorganic nitrogen (N) content (NH₄⁺ + NO₃⁻) was quantified using KCl extraction procedure and flow injection analysis. Other soil nutrients content was determined based on Mehlich-3 extraction procedure followed by ICP. A strong positive correlation between the GreenSeeker NDVI (NDVI-GS) and aerial
images derived NDVI (NDVI-Al) was obtained with a coefficient of determination ($R^2$) value of 0.63. Adjustment of NDVI with, number of days, cumulative growing degree days, and number of days with positive growing degree days, from planting to sensing increased the $R^2$ values up to 0.76, 0.76 and 0.73, respectively. The NDVI-GS obtain a stronger linear relationship with CC dry biomass and N content than NDVI-Al. Good positive correlations ($0.48 > R^2 > 0.12$) were found between NDVI and some macronutrients (P and K) and micronutrients (Mn and Cu). Overall, there was no significant effect of planting method and seeding rate observed on cane yield and quality parameters. Moreover, there was no statistical difference on CC nutrient removal rate among the treatments ($p>0.05$). For plant cane, the average cane and sugar yield across sites was 96 Mg ha$^{-1}$ and 10794 kg ha$^{-1}$, respectively. Lower yield was attained by the ratoon crops averaging only at 71 Mg ha$^{-1}$ cane yield and 7197 kg ha$^{-1}$ sugar yield. Remote sensing is a promising and viable technique to estimate CC biomass and nutrient uptake. Finally, this study corroborates the long-term effect of CC on nutrient management and their effect on cane yield and quality parameters.
CHAPTER 1. INTRODUCTION

Sugarcane (*Saccharum* spp.) is a grass, grown primarily for its sugar content (Schmitz et al., 2017). It is a tall perennial tropical grass producing tillers with unbranched stems of approximately 2 meters in height or taller and a diameter of 5 cm. Sugar is extracted from its thick stems called stalks (James, 2004). Sugarcane is an essential sugar and bioenergy industrial crop (Zhao & Li, 2015). The plant converts radiant energy into chemical energy very efficiently because it fixes carbon dioxide (CO$_2$) via C4 photosynthetic pathway (Santos et al., 2015). *Saccharum* is the sugarcane’s genus with has five existing species (Barnes, 1973) three of which are cultivated (*S. officinarum*, *S. barberi*, and *S. sinense*) while the two are classified as wild (*S. spontanum* and *S. robustum*) (Barnes, 1973; Vaughan, 2003). Sugarcane is grown widely by farmers of smallholdings in Asia, but most production is from large farms and plantations in Brazil, the rest of Latin America, SubSaharan Africa, Australia, and the USA (Fischer et al., 2014).

The economic value of sugarcane is attributed to its high productivity, efficient use of agricultural inputs, and having the possibility to be locally processed into added-value products (Moore & Botha, 2014). Globally the principal use of sugarcane is for crystal sugar production destined for human consumption (O’Hara & Mundree, 2016). Brazil, China, India, and Thailand are the four major sugarcane-producing countries responsible for 70% of the world’s productions with Brazil accountings for approximately 30% of this production (de Matos et al., 2020). In the USA, the production is concentrated in the southern states such as Louisiana, Florida, and Texas (Garrett, 2018). The National Average Statistical Service of the United States Department of Agriculture recorded
379,393 hectares of sugarcane harvested in the USA for the year 2021 equaling to 29,900 Mg of cane and an average yield of 78.9 Mg of sugarcane per hectare (USDA-NASS, 2022a). Louisiana is the country’s second-largest sugarcane producer after Florida (Schmitz et al., 2020). Since 1795, sugarcane has been a part of Louisiana’s economy (Kim & Day, 2011; Vaughan, 2003).

Sugarcane is propagated vegetatively from cuttings called billets or stalk which contains eyes or buds that will develop into the first stem and later produce shoots (Bakker, 1999). The harvesting in Louisiana usually takes place before the crop is physiologically matured (Greenland, 2005). In comparison to other sugarcane growing locations, where the sugarcane growing season can last more than 12 months, the sugarcane growing season in Louisiana is normally only nine months (Lofton et al., 2012). There are two cycles in sugarcane production system: the plant-cane cycle which starts with planting and ends after the first harvest and the ratoon, or ratoon-cane, cycle which starts after the harvest of the plant cane and continues with successive ratoon crops until field renewal (Cheavegatti-Gianotto et al., 2011). Sugarcane yield decline with crop age is one of the concerns in the industry that appears to be linked to unfavorable changes in soil biota as well as soil physical and chemical properties (Garside & Bell, 2011). Production and sustainability concepts in plant nutrition should not be regarded as mutually exclusive (Moore & Botha, 2014). Sugarcane has essentially four growth phases: germination, tillering, grand growth period and ripening, each phase typically requires 1 to 12 weeks (Hunsigi, 1993). Sugarcane is vegetatively propagated, and the commercial portion of the crop produced is vegetative as well. As a result, most sugarcane research is done when the culms and leaves are still growing and developing. Moreover, sugarcane has more
developmental stages or phenology. These stages are germination or sprouting, leaf development of the main shoot, tillering and side shoots, stem elongation, vegetatively propagated organs, emergence of inflorescence, flowering, development of fruit, ripening of seed, senescence and dormancy (Moore & Botha, 2014).

Under the Louisiana sugarcane production system, after ploughing out the last ratoon crop the field is left fallow until planting in August or September. By the time the first winter freeze arrives, the new shoots have grown to around 1 m tall. A hard freeze can kill (die back) newly established cane crop unlike in a year with a mild winter where sugarcane remains green. During the next spring, new sprouts emerge from the below-ground biomass called the plant-cane crop. Maximum growth rates occur in June, July, and August. In late August, the plant is roughly 2.5–3.0 m tall with a thick canopy. Harvest takes place from late September to early January (Greenland, 2005). In 2020, the most grown variety in the state was L 01-299 occupying 59% of the production areas followed by HoCP 96-540 (12%), L 01-283 (10%), HoCP 09-804 (9%), HoCP 04-838 (3%) and others (7%) (Gravois, 2021).

The high demand of sugarcane for soil nutrients foreshadows a loss of soil fertility specifically in monocropping systems with poor fertilization program and crop residues management (Hunsigi, 1993). Cane has the ability to rapidly deplete mineral elements in the soil, notably nitrogen (N) and potassium (K) (Meyer, 2013). Hence, sugarcane nutrition and fertilization for these primary nutrients should be continuously improved (de Matos et al., 2020). On an average, 100 tons per hectare cane production removes 208, 53, 280 and 30 kg of N, phosphorous (P), K and sulfur (S), respectively from the soil (Zende, 1990; Vennila et al., 2021). Others reported that the nutrient requirements to
match the 100 Mg ha\(^{-1}\) cane stalk yield run for 143, 43 and 210 kg ha\(^{-1}\) of N, P\(_2\)O\(_5\) and K\(_2\)O respectively (Orlando, 1993; Santos et al., 2015). It should also be mentioned that sugarcane needs a greater quantity of S than P (Santos et al., 2015). Moreover, Moore & Botha (2014) noted that 122, 17, 208, 27, 18, and 25 kg ha\(^{-1}\) of N, P, K, calcium (Ca), magnesium (Mg) and S, respectively was contained in sugarcane biomass for a cane yield of 93 Mg ha\(^{-1}\) and approximately 50% of these nutrients will be exported from the harvested field. The differences in soil productivity potential is confounded by the significant variation among the sugarcane genotypes with respect to nutrient use efficiency (Vennila et al., 2021), therefore fertilizer recommendations for sugarcane has to be validated routinely.

Sugarcane is one of the greatest consumers of fertilizers and responds well to fertilizers, therefore research on sugarcane nutrient requirements and fertilizer usage efficiency has been a focus since early days (Gopalasundaram et al., 2012). The fertilizer requirement of sugarcane differs between plant cane and ratoon crops wherein smaller doses of N and larger quantities of P and K are recommended for plant cane, and high N and K doses are for ratoons (Santos et al., 2015). Higher stalk yields demand higher amounts of N and K (Oliveira et al., 2016). However in Louisiana, P fertilizer is not commonly recommended to sugarcane (Johnson et al., 2017). Also, N fertilizer rates vary based on crop age and soil texture, therefore fertilizer should be administered according to the proper parameters to avoid excessive runoff and leaching (Gravois et al., 2011). Nitrogen rates for sugarcane in Louisiana are between 67-112 kg ha\(^{-1}\) for plant cane and between 90-135 kg ha\(^{-1}\) for ratoon. Phosphate rate are between 45-56 kg ha\(^{-1}\) for plant cane and between 45-67 kg
ha$^{-1}$ for ratoon. Potash rates are between 90-135 kg ha$^{-1}$ for plant cane and between 90-157 kg ha$^{-1}$ for ratoon (Gravois et al., 2014).

Runoffs of agronomic inputs from the field and improper disposal of (sugar) processing wastes have detrimental impact on the health of aquatic systems within and around sugarcane production and processing zones (Biggs et al., 2013; Omwoma et al., 2014). Chemical fertilizers are extremely soluble, they are taken by the earth faster than they are absorbed by the targeted plants, resulting in groundwater contamination (Alori et al., 2020). The primary difficulties facing sugarcane cultivation and processing are eutrophication, algal blooms, biodiversity loss and/or mortality of aquatic creatures, damage of water transportation, and low-quality household water (Webb, 2014). Nutrient levels should be optimized to maximize crop yields while limiting nutrient migration into surface and groundwater (USDA Natural Resources Conservation Service (NRCS), 2013).

The proper use of natural resources like soil must allow for economically and environmentally sustainable yields, which can only be achieved if soil health is maintained or restored (Cardoso et al., 2013). Soil quality refers to a soil's ability to function within ecological bounds and sustain a certain purpose, such as crop production (Laishram et al., 2012; Hermans et al., 2021). Soil health, on the other hand, refers to the soil's ability to operate as a living system that can sustain plant, animal, and human life (Laishram et al., 2012; Hermans et al., 2021). Moreover, it is considered a crucial element in enhancing agricultural production, environmental sustainability, and food system resilience (Stevens, 2018; Rejesus et al., 2021). Soil health practices include, cover cropping, no-
till residue and tillage management, conservation crop rotations, mulching, and nutrient management (Rejesus et al., 2021).

The use of bulky manures (manure, compost, press mud and vinasse) and green manuring, are important components of sustainable agriculture (Hunsigi, 1993). According to Das et al. (2020) including green manuring crops into cropping systems not only improves crop production and soil properties but it also conserves soil moisture and reduces weed infestations.

Cover cropping is an old management strategy but has suddenly become popular all over the world in recent years. The renewed interest on cover cropping has been associated with the essentiality of conservation agriculture approaches that promote sustainable farming and support ecosystem services (Romdhane et al., 2019). Cover cropping has been an ancient practice utilized by farmers in several places. More than a hundred years ago, Morgan & Taylor (1915) defined a cover crop (CC) as “a crop usually planted in the late summer or autumn, that will provide green, growing cover for the land during the late autumn and winter months”. More recently new definitions have been made like the one made by Benedict et al. (2014) staying that plants grown to cover and enhance the soil are known as cover crops (CC).

Cover crops improve soil organic matter, organic carbon sequestration, physical, chemical, and biological properties, nutrient cycling, weed suppression, insect management, wildlife habitat and diversity, and soil and wind erosion control (Adetunji et al., 2020). Beneficial effect of CC depends on proper timing of CC termination and incorporation (into the soil), and appropriate choice of CC species and mixes (Tonitto et al., 2006).
Cover crop cultivation can increase N levels and improve N cycling while lowering the risk of field and economic losses (O’Reilly et al., 2012). Legume CCs provided substantial amounts of plant-held N to succeeding crops (Thilakarathna et al., 2015; Adetunji et al., 2020). Winter CC can reduce nitrate-N (NO$_3^-$-N) losses in annual cropping systems by sequestering N in the spring (Heggenstaller et al., 2008). In contrast, other studies found no differences in soil total N with or without CC (Villamil et al., 2006). Moreover, planting nonlegume species increased carbon pools while legumes increased labile N pools (Sainju et al., 2003). Grasses and other non-legumes CC species do not fix N, although they can absorb it fast as they develop (Thorup-Kristensen, 2006) therefore, they are considered efficient at scavenging N. For this reason, their development is frequently restricted by N deficiency, thus combining a legume and a non-legume in a CC mixes can result in higher biomass output without compromising N scavenging capacity (Dabney et al., 2001).

Some CC species can sequester large amounts of nutrients other than N in their biomass. For example, rye and white mustard residues raised soil P and Mg levels, whereas oilseed rape mulch enhanced soil K levels (Harasim et al., 2016). Tchech et al. (2017) showed that soil P and K levels were affected by winter cover cropping. Also winter CC had influenced soil micronutrient pools, particularly zinc (Zn) and copper (Cu) (Dube et al., 2014).

Legume CC sown over the winters when sugarcane is in the ground can supply more than 112 kg of N per hectare (Gravois et al., 2011). No differences on sugarcane yield were observed after using summer CC, this can be explained because following the first ratoon cane cycle, the effects of CC are minimized, thereby reducing the differences
(Lovera et al., 2021). Cover cropping effects varied, but on average, resulted in the production of sugarcane stalks with higher sucrose content but of similar tonnage, when compared to the sugarcane following a fallow (White et al., 2020). Fixation of large amounts of N may be problematic if uncontrolled mineralization under warm and wet conditions takes place as this can lead to large NO$_3$-leaching losses in the weeks or months after the CC are terminated (Di Bella et al., 2021).

Broadcast seeds face different growing conditions than drilled seeds which impacts their germination and productivity (Koehler-Cole & Elmore, 2020). Planting by broadcasting requires less effort, may be less expensive than drilling, and can free up time for other tasks (Wilson et al., 2014; Koehler-Cole & Elmore, 2020). With these advantages, broadcast CC seeds can be established sooner which may collect more growing degree days and precipitation than drill-seeded CC resulting in higher biomass by the former (Koehler-Cole et al., 2020). Other found drilling seed a more effective technique for establishing CC than broadcasting on the basis of a better seed-to-soil contact (Fisher et al., 2011; Haramoto, 2019).

Seeding rates can be determined based on the amount of biomass desired or the cost of seeds (Haramoto, 2019). However, compensation effect should be taken into consideration. Earlier study showed that seeding rate had no effect on aboveground dry matter accumulation that was later ascribed to compensatory growth during the season in monocultures (Boyd et al., 2009). Similar compensation effect was described by Haramoto (2019) wherein lower initial plant density in low seeding rates was noted, but in the end produced similar biomass yield as the than high seeding rate. However in mixed CC species, total biomass increased with the seeding rate (Brennan & Boyd, 2012).
Precision conservation is a phrase that has evolved to describe techniques to soil and water conservation in agricultural and natural areas that use a mix of spatial technology (such as global positioning systems, remote sensing, and geographic information systems) and processes (such as map analysis, surface modeling, spatial data mining) (Berry et al., 2005; Capmourteres et al., 2018). Precision conservation is related to precision agriculture in the use of technology and principles to control the spatial and temporal variability of all elements of agricultural production in order to improve crop performance and environmental quality (Pierce & Nowak, 1999). Precision agriculture can be aided by remote sensing technology that enables the non-destructive collection of information about the earth’s surface (Liaghat & Balasundram, 2010). Remote sensing tools can provide key contributions to agriculture monitoring (Segarra et al., 2020).

Remote sensing indices that measure plant greenness based on reflectance in the near-infrared (NIR) and visible wavelengths are often used to estimate aboveground biomass (Gitelson, 2004). Remote systems sample the radiance field reflected or emitted by canopies at spatial resolutions and frequencies suitable for such applications (Baret et al., 2006). It provides a tool for rapid estimation of CC biomass production on working farms throughout the landscape (Hively et al., 2009). The use of remote sensing to monitor cropping techniques has been proved to be beneficial (Bégué et al., 2018).

Recent advancements in remote sensing technology and spectral reflectance analysis utilizing a variety of platforms (e.g., satellites and manned aircraft) may allow for faster estimates of CC growth and nutrient uptake (Yuan et al., 2019). Sensors in the visible and NIR spectral domains are available on a variety of platforms, including satellites, aircraft, balloons, tractors, and hand-held devices (Baret et al., 2006).
However, there have been relatively few studies that have evaluated the efficacy of various vegetation indices (VI) in predicting biochemical and biophysical properties in CC. (Yuan et al., 2019). Chemical and morphological features of the surface of organs or leaves affect the reflectance of vegetation to the electromagnetic spectrum (spectral reflectance or emission characteristics of vegetation) (Xue & Su, 2017). Vegetation indices are algebraic combinations of many spectral bands, designed to highlight vegetation physiological properties (i.e., leaf area, canopy biomass, absorbed radiation, chlorophyll content, photosynthetic capacity, and water status) (Gutierrez-Rodriguez et al., 2005; Candiago et al., 2015).

The normalized difference vegetation index (NDVI) is the most widely used VI, and it is based on the difference between the maximum absorption of radiation in red band (R) due to chlorophyll pigments and the maximum reflectance in the NIR spectral range due to leaf cellular structure (Tucker, 1979; Karnieli et al., 2010). The NDVI values range from -1 to 1, with negative values indicating a lack of vegetation (Pettorelli et al., 2005). Green vegetation values varies from 0.2 to 0.9, where shrub and grassland have moderate values (0.2–0.3), whereas woods and crops have greater values (0.4–0.9) (Candiago et al., 2015). Computing NDVI is represented in the following equation:

\[ NDVI = \frac{(\rho_{NIR} - \rho_{R})}{(\rho_{NIR} + \rho_{R})}, \]

where \( \rho \) is the reflectance in the respective band.

Active optical sensors employ modulated light emitting diodes to irradiate a plant canopy and monitor a part of the energy reflected from the canopy, instead of depending on ambient sunlight (Holland et al., 2012). Active canopy sensors have been shown to be
efficient in forecasting N status and yield in several crops (Ji et al., 2020). GreenSeeker®, an active-light sensor that is self-illuminated in R (660 ± 25 nm) and NIR (770 ± 25nm) bands (Trimble, 2010), measures the returned fraction of the emitted light in the sensed area through a detector, which is then used to calculate NDVI (Shanahan et al., 2008).

Passive sensor systems rely on sunlight as a light source, whereas active sensors are fitted with light-emitting components that provide radiation in specified waveband regions (Erdle et al., 2011). Passive sensors, on the other hand, require adequate ambient light to identify the target (Holland et al., 2012). Sunlight-based (passive) remote sensing is affected by variable sky conditions such as pollution, dust, clouds and changing solar zenith angle (Fitzgerald, 2010).

Unmanned aerial vehicles (UAVs), also known as unmanned aerial systems (UAS), are a fast-advancing technology that is gaining traction, mostly because they can carry a vast range of sensors meaning an almost limitless number of applications (Holman et al., 2016). The development of UAVs mounted with multispectral cameras (passive sensors) has enabled acquisition of high-resolution images across large areas quickly and repeatedly, at lower cost, and with greater flexibility in terms of flying heights and mission timing compared to satellite and manned aircraft platforms (Pajares, 2015). The combination of a UAV and multispectral sensor is a successful tool for nondestructive estimation of CC biomass and N uptake (Yuan et al., 2019).

Limited research has been conducted to elucidate the differences in CC seeding rates and the seeding method for nutrient management for sugarcane while a sensor-based model for CC biomass and nutrient turnover has not been developed. For these reasons, this study was designed to: 1) evaluate the use of NDVI for predicting CC biomass and
nutrients turnover and 2) determine the impact of planting method and rate of CC on soil nutrients levels and on sugarcane yield and sugarcane quality components.
CHAPTER 2. EVALUATE THE USE OF NDVI FOR PREDICTING COVER CROPS BIOMASS AND NUTRIENTS UPTAKE

2.1. INTRODUCTION

A suitable and efficient crop evaluation method needs new technology such as remote sensing that offers a nondestructive synoptic screening capabilities (Ennouri et al., 2019). Near-real-time monitoring is required to optimize in a sustainable manner agricultural management practices (Areal et al., 2018; Weiss et al., 2020). Because it provides a non-destructive means of supplying information, remote sensing looks to be an important tool for dealing with the mentioned problem (Weiss et al., 2020).

The American Society for Photogrammetry and Remote Sensing (ASPRS) defined remote sensing as: “the measurement or acquisition of information of some property of an object or phenomenon, by a recording device that is not in physical or intimate contact with the object or phenomenon under study” (Colwell, 1983; Jensen, 2016). It is an approach to measure certain properties at a distance, relying on propagated signals like electromagnetic radiation rather than in situ measurements (Schowengerdt, 2012).

There are two forms of interaction between a sensor and the Earth's surface: active, where sensors generate its own energy to light the objects and record the reflectance values; and passive, where solar radiation is used to illuminate the Earth's surface and detect reflections (Zhu et al., 2018). Passive sensors, require adequate ambient light to identify the target (Holland et al., 2012). The measured signal by passive sensing will always be impacted by the lighting conditions (Trotter et al., 2010). These sensors are affected by variable interferences such as pollution, dust, clouds and others (Fitzgerald, 2010). Active sensors are usually mounted directly on the machines and use visible light
(e.g., red) and near-infrared (NIR) reflectance measurements to assess plant nitrogen (N) status in real time (Mezera et al., 2021). The main benefit of proximal active sensors is that they have their own light source with synchronous detection thus, they can operate independently from the environmental light conditions, even at night (Lamb et al., 2009). However, the limited power output and detection sensitivity limit the use of these sensors up to a few meters above the target (Lamb et al., 2009). On the contrary, passive sensors are not restricted by the mentioned limitation and can be mounted on different platforms covering larger areas in shorter times.

Remote sensors can also be divided into two types: imaging and non-imaging sensors (Zhu et al., 2018). An aerial image is one of the outputs of an imaging sensor, although there are many various types of aerial photos that may be acquired, ranging from black-and-white to color formats (Ferguson & Rundquist, 2018). On the other hand, a non-imaging sensor measures the signal of the intensity of the whole field of view of the device, that is why variability across the field of view is not recorded (Zhu et al., 2018).

The conversion of a reflectance spectrum into a single number value, known as a vegetation index (VI), is a common method of determining vegetation attributes (Thenkabail et al., 2018). One purpose of vegetation indices is to increase sensitivity to vegetation features (Liang et al., 2012). A number that qualifies the intensity of a phenomenon that is too complicated to be reduced into known parameters is called an index (Bannari et al., 1995). Indices have a higher sensitivity for detecting biomass than individual spectral bands (Asrar et al., 1984; Bannari et al., 1995). They are algebraic combinations of various spectral bands that are intended to emphasize physiological characteristics of vegetation (Gutierrez-Rodriguez et al., 2005; Candiago et al., 2015).
Vegetation indices are based on the linear combination or transformation of canopy reflectance measurements utilizing two or more distinct wavebands, which are expressed in ratios (e.g., simple ratio or SR) and normalized forms (e.g., normalized difference vegetation index or NDVI) (Tubaña et al., 2011).

Several vegetation indices were conceived to estimate vegetation biochemical and biophysical variables, like plant pigments, biomass and leaf area index (Xiao et al., 2014). Tucker (1979) point out that the red light (630-690 nm) is absorbed by chlorophyll, and the NIR light (760-900 nm) is substantially reflected by leaf cellular structures. Vegetation indices derived from canopy reflectance within the NIR and the visible light wavebands have a good relation with crop biophysical parameters (Tubaña et al., 2011).

Rouse et al. (1974) developed what they referred early as the vegetation index, later called NDVI, computed as the difference of the reflectance values at the NIR and the red band, divided by their sum. The NDVI has a strong relationship with the plant leaf area index (Wiegand et al., 1992), and has been effectively utilized to quantify wheat (Triticum aestivum) crop biomass, yield, N status, chlorophyll content, and photosynthesis capability (Wiegand et al., 1992; Benedetti & Rossini, 1993; Hansen & Schjoerring, 2003; Reyniers & Vrindts, 2006). Remote sensors, such as Earth orbiting satellites, cameras mounted on different aircrafts, proximal sensors, and other methods can be used to obtain VI (Prabhakara et al., 2015).

Unmanned aircraft vehicles such as drones, have proven their applicability for timely surveillance and evaluation of vegetation status because: (1) they can fly at low altitudes and deliver ultra-high resolution aerial imagery, enabling detection of small vegetation, (2) flights can be planned with flexibility based on key moments caused by vegetation
progression, and (3) they can acquire different regions of vegetation spectrum using various sensors (Dandois & Ellis, 2013; de Castro et al., 2021). Visible light and multispectral sensors were suited to recognize abiotic stress (e.g., N deficiency) beside this require detecting small changes in leaf pigments levels (de Castro et al., 2021). However, less effort has been made to use UAVs to explore within-field variations in cover crop development or N uptake prior to termination (Hunt et al., 2011; Roth & Streit, 2018).

Another type of instrument commonly used in precision agriculture to identify N deficiencies and biomass production, is the active light sensor, which measures reflectance in the red-to-infrared portion of the light spectrum (Kornecki et al., 2012). In recent years, sensors to measure agricultural crop canopy NDVI have become commercially available, including a low-cost handheld meter (e.g., GreenSeeker HCS-100, Trimble Navigation) (White et al., 2019). The GreenSeeker® is an active sensor which emits light and captures reflectance at the red and NIR wavebands. Remotely sensed measures of spectral reflectance and indices derived from these measures, such as NDVI have been used successfully to predict agricultural plant biomass. (Muñoz et al., 2010). White et al. (2019) and Muñoz et al. (2010) demonstrated that a handheld NDVI meter can accurately predict CC N content across a wide range of plant species.

To establish a relationship between the sensing measurement (i.e., radiance) and the physicochemical attributes (agronomic variables like biomass and leaf N content), they must be modelled in order to deduce the latter from the sensing data (Weiss et al., 2020). Empirical models are those that use pure statistical methods to link inputs and outputs (Baker et al., 2018; Weiss et al., 2020). Purely empirical procedures, often known as "regressions," include calibrating a numerical connection between one or more observed
biophysical variables and the remote sensing signal or its numerical translation (Weiss et al., 2020). Most of the current agricultural production forecasting relies on linear statistical models, which are unable to account for nonlinear relationships in the data, ignoring the complexity of the agricultural ecosystem (Johnson et al., 2016). The former technique has the advantage of being simple, but it comes at the cost of obtaining ground data (such as yield and reflectance) and a likely lack of extrapolation capacity in time and space (Weiss et al., 2020).

Linear models linking in situ data to simple numerical transformations of remote measurements, combined with accessible auxiliary information, may be sufficient when the goal is to forecast in situ quantities rather than comprehend radiate transfer processes (Fernandes & Leblanc, 2005). Crop yields and N content were estimated using VIs in the sun spectral domain with empirical methods (Clevers & Gitelson, 2013; Johnson et al., 2016; Delloye et al., 2018; Weiss et al., 2020).

Precision agriculture practices that employ remote sensing technologies are becoming more common. Sensor-based practices like, in-season fertilizer recommendation, weed management, yield predictions among others are used mostly in cash crops. Giving more uses for these sensors, i.e., using them to sense CC during the winter, make the adoption of these tools more profitable. Therefore, this study was established to determine the relationship of sensor VIs with CC biomass and nutrient uptake. This procedure is required to establish sensor-based prediction models for nutrient turnover from cover cropping.
2.2. MATERIALS AND METHODS

2.2.1. Site Description, planting method, treatment structure and trial establishment

Five field sites were utilized for this project, two conducted from September 2019 to December 2020 and the rest from August 2020 to December 2021 at the LSU AgCenter Sugar Research Station in St. Gabriel, Louisiana (Latitude 30°, 15’, 13” N; Longitude 91°, 06’, 05” W). Data on soil surveys was obtained via the soil survey website from the Natural Resources Conservation Service (NRCS). Sites 1 and 3 were on fields with Commerce silt loam soil. Sites 2, 4 and 5 were on fields with a mixture of Commerce silt loam and Commerce silty clay loam soils. These soils have a taxonomic classification as Fine-silty, mixed, superactive, nonacid, thermic Fluvaquentic Endoaquepts (Soil Survey Staff, 2021). These are flood plain Inceptisols, poorly drained, saturated for some time of the year, with high-water table (Soil Survey Staff, 2015). Weather data was gathered from the National Oceanic and Atmospheric Administration (NOAA). Climatic characterization was done using Global Summary of the Month (GSOM) data.

Site 2 differs from the rest of the sites in terms of data collection caused by misunderstanding issues related to management practices. Cover crops were terminated and incorporated into the soil before biomass and remote sensing data were gathered. However, this inconvenient affected data collection for the purposes of these objective, the other study did not get altered.

All sites were planted with sugarcane variety L 01-299. This variety is one of the most predominant varieties in Louisiana. It was derived from the cross made between L 93-365 as the female parent and LCP 85-384 as the male parent (Gravois et al., 2011).
Soil was mechanically disked, with 1.2 m wide beds and 0.3 m height approximately. Sugarcane stalks between 1.2 and 1.7 m of length were cut with a whole stalk harvester and loaded to a tractor wagon. Stalks were planted by hand placing up to four stalks side by side into an open furrow with approximate 10 cm of overlapping ends. The furrows were then covered with soil and compacted with a custom roller packer. Sites had 1.5 m (5 ft) alley gaps (with no stalks) to separate treatment plots.

The treatment structure was composed by eight combinations of different CC planting methods (broadcast and drilling) and seeding rates (100%, 50%, 25%, 0 of the recommended rates by NRCS). The treatment structure is presented in Table 2.1. Each treatment was replicated four times in each site. Treatments at site 1 had a completely randomized design (CRD) with plots of 12 m (40 ft) long and 5.5 m (18 ft) (3-row) wide whereas treatments at sites 2 to 5 had a randomized block design (RBD) with plots of 15 m (50 ft) long and 5.5 m wide.

For this study five CC species were planted in a mix, a month after sugarcane was planted. Three were legumes, hairy vetch (Vicia villosa), crimson clover (Trifolium incarnatum) and balansa clover (Trifolium balansae). The other two species were brassicas, tillage radish (Raphanus sativus var. niger) and rapeseed (Brassica rapa). Cover crops seeding rates are presented in Table 2.2
Table 2.1. Treatment structure of the study established at the LSU AgCenter Sugar Research Station in St. Gabriel, LA

<table>
<thead>
<tr>
<th>Treatment Number</th>
<th>Planting Method</th>
<th>Seeding Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Broadcast</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Broadcast</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>Broadcast</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>Broadcast</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>Drilling</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>Drilling</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>Drilling</td>
<td>50</td>
</tr>
<tr>
<td>8</td>
<td>Drilling</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 2.2. Cover crop species and seeding rates planted for the different treatments (planting method and NRCS rates) per site, 2019 and 2020, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Planting method</th>
<th>Seeding rate</th>
<th>Crimson Clover</th>
<th>Balansa clover</th>
<th>Hairy vetch</th>
<th>Tillage radish</th>
<th>Rapeseed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1-2</td>
<td>2019</td>
<td>Broadcast</td>
<td>100%</td>
<td>11.21</td>
<td>5.60</td>
<td>13.45</td>
<td>2.24</td>
<td>2.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>5.60</td>
<td>2.80</td>
<td>6.73</td>
<td>1.12</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>2.80</td>
<td>1.40</td>
<td>3.36</td>
<td>0.56</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Drilling</td>
<td>100%</td>
<td>6.73</td>
<td>4.48</td>
<td>8.97</td>
<td>1.12</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>3.36</td>
<td>2.24</td>
<td>4.48</td>
<td>0.56</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>1.68</td>
<td>1.12</td>
<td>2.24</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Site 3-4-5</td>
<td>2020</td>
<td>Broadcast</td>
<td>100%</td>
<td>8.56</td>
<td>19.84</td>
<td>13.45</td>
<td>2.27</td>
<td>2.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>4.28</td>
<td>9.92</td>
<td>6.73</td>
<td>1.13</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>2.14</td>
<td>4.96</td>
<td>3.36</td>
<td>0.57</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Drilling</td>
<td>100%</td>
<td>6.84</td>
<td>11.90</td>
<td>8.97</td>
<td>1.13</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>3.42</td>
<td>5.95</td>
<td>4.48</td>
<td>0.57</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>1.71</td>
<td>2.98</td>
<td>2.24</td>
<td>0.28</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Note: 100% seeding rates for all the cover crops species are based on NRCS recommendation.

2.2.2. Biomass determination

Cover crop biomass was collected using the quadrant frame method. The quadrant (1 x 1 m²) was placed randomly three times in each plot, resulting in three subsamples per plot. Collection was done in early spring, in March and April. Above ground biomass was
collected from each species including native weeds, in addition of the roots of the tillage radish. Cover crop biomass were separated by species and placed in paper bags for later recording of the fresh weight. Dry weight was recorded after samples were oven dried at 65°C. Then, samples were ground and sieved to pass 1 mm size particle.

Dry biomass per specie was computed as follow:

\[
CC \text{ Dry Biomass (kg ha}^{-1}\) = Dry biomass weight (kg m}^{-2}\) \times 10,000 (m^2 \text{ ha}^{-1})
\]

Cover crops were terminated through herbicide application and later incorporation, between March and April as shown in Table 2.3. Herbicide application was done with a mix of metribuzin [4-Amino-6-(1,1-dimethylethyl)-3-(methylthio)-1,2,4-triazin-5(4H)-one] at 4 kg a.i. ha\(^{-1}\) and pendimethalin [N-(1-ethylpropyl)-3,4-dimethyl-2,6-dinitrobenzenamine] at 3 kg a.i. ha\(^{-1}\). Incorporation was done two weeks after herbicides were applied, furrow and row shoulders were cultivated using a three-row disk sugarcane cultivator.

Table 2.3. Dates of field activities for the cover crop treatments for all sites at LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Site</th>
<th>Planting date</th>
<th>Sensing date</th>
<th>Biomass sampling</th>
<th>Termination date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>November 6, 2019</td>
<td>March 5, 2020</td>
<td>March 5 - 6, 2020</td>
<td>March 11, 2020</td>
</tr>
<tr>
<td>2</td>
<td>November 6, 2019</td>
<td></td>
<td></td>
<td>March 18, 2020</td>
</tr>
<tr>
<td>3</td>
<td>September 17, 2020</td>
<td>March 8, 2021</td>
<td>March 8, 2021</td>
<td>March 16, 2021</td>
</tr>
<tr>
<td>4</td>
<td>October 30, 2020</td>
<td>March 8, 2021</td>
<td>March 10, 2021</td>
<td>March 16, 2021</td>
</tr>
<tr>
<td>5</td>
<td>October 30, 2020</td>
<td>April 8, 2021</td>
<td>April 8, 2021</td>
<td>April 12, 2021</td>
</tr>
</tbody>
</table>

**2.2.3. Plant tissue analysis**

Plant tissue composition was analyzed through the nitric acid-hydrogen peroxide (HNO\(_3\)-\(H_2O_2\)) digestion method followed by inductively coupled plasma (ICP) analysis. Dry ground plant tissue samples (0.5 g) were weighed onto approximately 5x5 cm Kim wipes,
enclosed by carefully twisting the four corners of wipes together then placed into the digestion tubes. Five (5) ml of HNO₃ (68-70% ACS reagent grade) was added into the tubes and allowed to stand for 50 minutes for later shaking with a vortex mixer. Digestion tubes were placed in the digestion block at a temperature of 150°C for 5 minutes. Tubes then were removed from the digestion block allowed to cool for 10 minutes before adding 3 ml of H₂O₂. The tubes were covered with small funnels and placed back into the digestion block for 165 minutes (2 hours and 45 minutes). Digested samples were then cooled down to room temperature. Digested solution was transferred into 15-ml centrifuge tubes and was brought to 12.5 ml with distilled water. Digested solution samples were filtered with Whatman No. 1 filter paper and transfer to 10 ml ICP tubes.

2.2.4. Plant total N analysis

Total N content in plant tissue was carried out using CN dry combustion method with LECO® CN628 analyzer (St. Joseph, MI). Dry ground plant tissue samples were weighed to 0.02 g placed on tin foil cups. Samples were loaded into the appropriate position of the sample carousel. Carbon and N present in the sample are oxidized into gases, water is removed, and gases collected into a ballast for equilibrium. Separate optimized non-dispersive infrared (NDIR) is used to detect C concentration in the form of CO₂. Nitrogen gases are reduced in copper to obtain N₂ and a thermal conductivity cell is used to detect N₂ concentration (LECO, 2016).

Nutrient content was analyzed and computed separately for each specie in each plot. Tillage radish was divided into leaves and roots for both analyses. Cover crops biomass nutrient content was determined for both macronutrients (N, P, K, S, Ca and Mg) and micronutrients (B, Cu, Fe, Mn, Mo, Ni and Zn) using the following equations:
\[ CC \text{ biomass macronutrient content (kg ha}^{-1}) = CC \text{ dry biomass (kg ha}^{-1}) \times \text{concentration (\%)/100} \]

\[ CC \text{ biomass micronutrient content (kg ha}^{-1}) = CC \text{ dry biomass (kg ha}^{-1}) \times \text{concentration (mg kg}^{-1})/10^6 \]

2.2.5. Remote sensing data collection and manipulation

Remote sensor data was collected between one to two weeks prior to cover crop termination. Ground-based sensor data was collected by consistently holding the GreenSeeker\textsuperscript{®} sensor head in a nadir position at 1 m above the canopy, while walking at a constant pace through each quadrat in each plot. Four wavelength regions were collected, as described in Table 2.4.

Aerial imagery was collected with a multispectral camera RedEdge-M by MicaSense mounted on a DJI Phantom 4 Pro Advance drone. Multispectral images were collected with five wavelengths regions, details presented in Table 2.3. The UAS was flown autonomously at an altitude of 30.48 m (100 ft) with an 80\% side and frontal overlap and collected images at a rate of 3.13 m s\textsuperscript{-1} (7 mph).

Flight planning and procedure were carried out through the DroneDeploy software. Flight preparation was done through the desktop version a couple days before data collection. Before launching the drone pictures of the Calibrated Reflectance Panel (CRP) were taken near the sites to calibrate the multispectral camera. Pictures of the CRP were taken in a flat surface and with the sensor towards the sun, avoiding shadows. These images were saved and used to normalize the data later. Pre-flight checklist was completed before launching the drone.
Table 2.4. Sensors spectral bands specifications.

<table>
<thead>
<tr>
<th>Band number</th>
<th>Band name</th>
<th>Center Wavelength (nm)</th>
<th>Bandwidth (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GreenSeeker® (Trimble Navigation)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Red660</td>
<td>660</td>
<td>25</td>
</tr>
<tr>
<td>2</td>
<td>Red710</td>
<td>710</td>
<td>25</td>
</tr>
<tr>
<td>3</td>
<td>Red735</td>
<td>735</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>Near Infrared</td>
<td>770</td>
<td>25</td>
</tr>
<tr>
<td><strong>RedEdge-M (MicaSense)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Blue</td>
<td>475</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>Green</td>
<td>560</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>Red</td>
<td>668</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>Near Infrared</td>
<td>840</td>
<td>40</td>
</tr>
<tr>
<td>5</td>
<td>Red Edge</td>
<td>717</td>
<td>10</td>
</tr>
</tbody>
</table>

Source: Adapted from Trimble (2010) & MicaSense (2017)

Construction of the orthomosaic was done through the Pix4D software after all data was gathered from each site, hereafter is termed site-year. The orthomosaic generation was done following the steps in the software, creation of the project, add images, image properties (image geolocation and camera model), select the output coordinate system (World Geodetic System 1984 as datum and WGS84/UTM zone 15N as coordinate system), processing options template (Ag Multispectral).

After all these steps but before starting the stitching process, radiometric processing and calibration was set up. For the radiometric processing and calibration (in the Processing Options icon, the Digital Surface Model (DSM), Orthomosaic and Index option under the Index Calculator tap) all five bands were corrected with pictures of the CRP, where reflectance factors were obtained. In some situations, reflectance factors were not able to be capture from the picture, in those cases recommended values per band by the provider were used as described: Blue=0.489, Green=0.49, Red=0.489, NIR=0.486 and
Red_edge=0.488. Resolution was set up as automatic (equal to the ground sampling distance (GSD), for this project 1.47 cm/pixel). GeoTIFF and merge tiles options were selected for the reflectance map. All five individual bands plus NDVI were checked as indices generated. The export grid size was modified to 5 cm/grid for index values as point shapefiles and index values and rates as polygon shapefiles, to end the radiometric processing and calibration set up.

The creation of the orthomosaic includes three main steps, 1) initial processing, 2) point cloud and mesh and 3) DSM, orthomosaic and index. The end results are presented in the index folder of the project, each band and NDVI has a reflectance map with an extension Tagged Image File Format (TIFF).

To ensure that the GreenSeeker readings and aerial image were taken from the same area after collecting the biomass red cardboard panels were placed on the square-meter area, to create color contrast for easier identification. A second flight was carried out then and consequently a second aerial image with red spots was generated. This helped us identified the exact same area in the first aerial image and compared according with readings taken by GreenSeeker sensor.

### 2.2.6. Data analysis

Aerial images, GreenSeeker and support geospatial data was processed in QGis (QGis.org, 2022). Statistical analyses were done with the use of R project (R Core Team, 2022) through the integrated development environment (IDE) R Studio, computation was done with the use of base R and tidyverse package (Wickham et al., 2019), and improved visualizations was done with ggpmisc (Aphalo, 2021) and GGally (Schloerke et al., 2021). Linear regression analysis was performed to stablish the relationship between sensing
data and CC variables for all site-years. The degree of linear relationship for each pair of variables was measured through the coefficient of determination ($R^2$).

2.3. RESULTS AND DISCUSSION

2.3.1. Climatic conditions

The total monthly precipitation and average monthly temperature for the Sugar Research Station in St. Gabriel obtained from the Baton Rouge Metro Airport weather station from 2019 to 2021 are reported in Figures 2.1 and 2.2, respectively. The key climatic factors influencing CC selection and potential utility are temperature and rainfall, the warmer and wetter the conditions the bigger the number of CC possibilities and advantages (Dabney et al., 2001).

For the first year of experiments, CC were planted in November 2019 and terminated in March 2020. During this period, the lowest monthly average temperature was $13.6^\circ C$ in January, and the highest was $21.3^\circ C$ in March, during termination (Figure 2.1). For site-years 3-5, CC were planted between September and October and terminated in March and April. The lowest temperature was $10.2^\circ C$ in February of 2021 and the highest was $21.9^\circ C$ in October 2020, at planting time. A freeze was recorded on February 16, 2021, with the lowest temperature of $-6.6^\circ C$.

The total precipitation in the first year of experiments was 460 mm (November, December, January, February, and March), with the highest monthly precipitation (158 mm) in February (Figure 2.2). For the second year of experiments, the total precipitation was 770 mm (October, November, December, January, February, and March), with the highest monthly value of 123 mm in March.
Figure 2.1. Monthly total precipitation (mm) from January to December 2019, 2020, and 2021 at the Sugar Research Station in St. Gabriel, LA.

Figure 2.2. Monthly average temperature (°C) from January to December 2019, 2020, and 2021 at the Sugar Research Station in St. Gabriel, LA.
2.3.2. Growing degree days

Planting CC earlier in fall allows for additional growing degree days (GDD) thus increasing CC biomass before winter dormancy (Mirsky et al., 2011; Lawson et al., 2015; Sedghi & Weil, 2022). Temperature base to compute GDD for CC is either 0°C or 4°C (Prabhakara et al., 2015). Base temperature of 0°C were used in models dividing fall and spring GDD (Baraibar et al., 2018; Baraibar et al., 2020). On the other hand, 4°C was used to compute GDD for the entire season (Mirsky et al., 2011; Brennan & Boyd, 2012; Lawson et al., 2015; De Notaris et al., 2018; Sedghi & Weil, 2022). For these experiments base temperature used was 4°C. Three main variables were computed to standardize the development of the CC through the season. The first one was the number of days (ND) from planting to sensing. The second one was the cumulative GDD (CGDD) as the sum of the GDD of all days from planting to sensing (computed as Equation 2.1). The last one, was the number of days with positive GDD (NP-GDD), as the sum of days that presented a positive GDD value, from the same period (GDD>0). Table 2.5 shows the values for each variable per site.

\[
CGDD = \sum(Daily \ mean \ air \ temperature - 4)
\]  \hspace{1cm} Equation 2.1

These use of factors to adjust NDVI measurements generally improved the model for yield predictions in grain crops (Raun et al., 2002; Teal et al., 2006).

Table 2.5. Number of days, cumulative growing degree days and number of positive days of growing degree days from planting to sensing day.

<table>
<thead>
<tr>
<th>Site</th>
<th>ND</th>
<th>CGDD</th>
<th>NP-GDD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>121</td>
<td>1208</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>173</td>
<td>1968</td>
<td>164</td>
</tr>
<tr>
<td>4</td>
<td>130</td>
<td>1170</td>
<td>121</td>
</tr>
<tr>
<td>5</td>
<td>161</td>
<td>1630</td>
<td>152</td>
</tr>
</tbody>
</table>
2.3.3. Cover crop biomass

Cover crop treatments imposed in all site-years produced a high range of dry biomass (Figure 2.3). A total of 316 samples (1 m² each sample) of biomass were collected through all site-years. The overall average of dry biomass was 765 kg ha⁻¹, with a standard deviation of 659 kg ha⁻¹, showing the high spread of the data. Even between each treatment, there was a high variability in terms of dry biomass. Means for dry biomass for the broadcast planting method were 841, 818, 790, and 656 kg ha⁻¹ corresponding to 100%, 50%, 25% and 0% of the seeding rate, with standard deviations of 715, 611, 746, and 648 kg ha⁻¹ respectively. Moreover, average dry biomass for the drilling planting method were 782, 828, 832, and 567 kg ha⁻¹ for to 100%, 50%, 25% and 0% of the seeding rate, with standard deviations of 518, 726, 773, and 473 kg ha⁻¹ correspondingly.

![Figure 2.3. Cover crop dry biomass yield at different planting methods and seeding rates at the Sugar Research Station in St. Gabriel, LA](image)

Figure 2.3. Cover crop dry biomass yield at different planting methods and seeding rates at the Sugar Research Station in St. Gabriel, LA
2.3.4. Linear regression between GreenSeeker and aerial imagery derived normalized difference vegetation index

The linear relationships between GreenSeeker and aerial imagery-derived NDVI (hereafter termed as aerial imagery-NDVI) are showed in Figure 2.4. The relationship between GreenSeeker and aerial imagery-NDVI (Figure 2.4. A) had a $R^2$ of 0.63, indicating that GreenSeeker-NDVI could explain 63% of the variation in the aerial imagery-NDVI. Moreover, the relationship was statistically significant, yielding a $p$-value lower than 0.001. Therefore, suggesting that the relationship between NDVI-AI and NDVI-GS is linear.

When merging locations and years, dividing NDVI measurements by CGDD was supposed to account for some of the site-specific growth conditions (Raun et al., 2001). To reduce the variation introduced by different cropping seasons between sites, all NDVI values were divided by ND (Figure 2.4. B) CGDD (Figure 2.4. C), and NP-GDD (Figure 2.4. D) prior to regression analysis. As a result, the $R^2$ of the linear relationships between GreenSeeker and aerial imager (adjusted) NDVI values increased from 0.63 to 0.73 and 0.76.

Plant development is influenced by climatic conditions such as precipitation and temperature as these influence water balance (Wang et al., 2003). A strong correlation was found between NDVI and CGDD, also with NDVI and soil temperature, reflecting the impact of available energy and heat for plant development (Yang et al., 1997). Likewise, Wang et al. (2003) mentioned that there is a strong correlation between climatic conditions and NDVI measurements.
According to Forestieri (2021) a considerable improvement was obtained by normalizing (dividing) the NDVI values with the CGDD; increasing the $R^2$, thus the amount of variation explained by the linear model. Moreover, incorporating CGDD to NDVI data, was essential for accounting for differences in crop phenological development and, providing a generic categorization model that could be used across seasons (Skakun et al., 2017). Despite the fact that the NDVI and NDVI/ND prediction equations were both effective, using NDVI/CGDD should be more consistent across varied field conditions and climates (Teal et al., 2006). Although utilizing CGDD and ND to correct NDVI data improved the accuracy of yield estimating models, only the CGDD modification improved the link between NDVI and cane tonnage because the CGDD adjustment offered a better estimate of temperature throughout the growing season than just the ND (Lofton et al., 2012). The NDVI measurement divided by NP-GDD would be another useful approach because this strategy eliminate the days when growth was not possible due to low temperature (Raun et al., 2005). It should be emphasized that when using the normalized NDVI, greater correlations for wheat (*Triticum aestivum*) grain production were found in the vegetative development phases (Cattani et al., 2017).
Figure 2.4. Relationships between GreenSeeker (GS) and aerial imagery (AI) derived NDVI readings of canopies of mixed species of cover crops before termination, 2020 and 2021, Sugar Research Station in St. Gabriel, LA. A) NDVI; B) NDVI value divided by the number of days (ND); C) NDVI value divided by the cumulative growing degree days (CGDD) and D) NDVI value divided by the number of positive days of growing degree days (NP-GDD) from planting to sensing.
Similar results were obtained in this study where $R^2$ was increased up to 0.73 - 0.76. Specially, the adjustments of NDVI by NP and CGDD resulted in improvement in $R^2$ from 0.63 to 0.76 and to 0.73 when NDVI was adjusted using NP-GDD. This indicates that approximately 76% or 73% of the variation in adjusted NDVI from one sensor can be explained by the adjusted NDVI from the other sensor. On those three cases $p$-values lower than 0.001 were obtained as well indicating a significant linear relationship of these adjusted NDVI values from GreenSeeker and aerial imagery.

2.3.5. Linear regression between cover crop dry biomass and normalized difference vegetation index derived from both sensors

The relationships between GreenSeeker and aerial imagery NDVI with CC dry biomass are shown in Figure 2.5. The relationship between GreenSeeker NDVI and dry biomass (Figure 2.5. A) had a $R^2$ of 0.45 and statistically significant ($p < 0.001$). On the contrary, the linear relationship between aerial imagery NDVI and CC dry biomass (Figure 2.5. B) was weak with a $R^2$ of 0.17, indicating that only 17% of the CC dry biomass variance can be explained by the linear relationship with the aerial imagery NDVI. However, the relationship was statistically significant suggesting that the CC dry biomass was (linearly) associated with aerial imagery NDVI.

Roth and Streit (2017) compared the performance of three VIs from passive sensors to estimate CC biomass wherein low correlations were obtained, however NDVI was better than red edge inflection point (REIP) and green red vegetation index (GRVI) for some species. Moreover, they indicated NDVI showed saturation when measurements were close to 0.7. Hunt et al. (2011) identified poor linear correlations between NDVI and CC biomass and NDVI from different sensors with the active sensor NDVI having the lowest
correlation. Nevertheless, the authors indicated that these poor relationships could have been caused by a small range of biomass and a greater within-strip variability than among experimental strips. On the other hand Yuan et al. (2019) obtained a strong correlation between CC biomass and NDVI measured by a passive sensor; mainly due to the small biomass (<1500 kg ha\(^{-1}\) CC biomass) at sensing time, thus avoiding saturation problems. For this study, saturation seemed had contributed for the relatively low correlations between NDVI and CC dry biomass (Figure 2.5). The NDVI readings did not proportionally increase when CC biomass samples were greater than 2000 kg ha\(^{-1}\). The NDVI from both sensors were not able to discriminate the amount of biomass samples above 2000 kg ha\(^{-1}\). Saturation issues with the NIR and red-band indices are common, restricting regression equations’ predictive accuracy (Thenkabail et al., 2000). Furthermore, Thenkabail et al. (2000) explained this issue indicating that a dense vegetation with full coverage, has biomass that is still growing. The quantity of red light absorbed reaches a maximum (hence approaching zero reflectance), but NIR scattering by leaves continues to rise (Tilly et al., 2015).

GreenSeeker NDVI had a better association with CC biomass compared with the aerial imagery NDVI. This can be attributed to the characteristics of the reflectance readings by each sensor. The intensity of the sunlight, bidirectional reflectance, surface roughness and other physical or ambient circumstances can all alter the reflectance gathered using passive light sensors compared to active light sensors (Lelong et al., 2008; Zhu et al., 2018). On the other hand, GreenSeeker is equipped with a pre-calibrated, active, optical light sensor, thus is unaffected by ambient conditions (Coker, 2019). An active sensor emits a known wavelength signal and gets the reflectance. On the other hand, a passive
sensor just obtains the reflectance of certain wavelengths, assuming the energy of the signal is constant and stable, which might not be the case, thus increasing the uncertainty of the sensor readings.

Figure 2.5. Relationships between GreenSeeker (A) and aerial imagery (B) NDVI and CC dry biomass, 2020 and 2021. Sugar Research Station in St. Gabriel, LA.

Aerosol scattering has a far greater impact on shorter wavelengths of the visible sun spectrum, such as blue or red than to NIR (Tan et al., 2020). Moreover, high wind speeds result in higher concentrations of soil-derived aerosols, which decrease IR resolution.
Water vapor absorption mostly impacts longer wavelength light, such as the NIR, and the sensitivity of various absorption peaks varies as water vapor concentration changes (Tan et al., 2020). These factors have a greater impact the longer the travel distance of the wavelength, affecting more in this case to the passive sensor.

2.3.6. Linear regression between nitrogen content of cover crop biomass and normalized difference vegetation index (NDVI) derived from both sensors

The results on linear regression analysis between GreenSeeker and aerial imagery NDVI and CC dry biomass N content are shown in Figure 2.6. The relationship between GreenSeeker NDVI and CC N content (Figure 2.6. A) had a $R^2$ value of 0.35, indicating that GreenSeeker NDVI could explain only 35% of the variation in the N content of the CC dry biomass ($p<0.001$). On the other hand, there was virtually no relationship between aerial imagery NDVI and N content ($R^2 = 0.008$, $p<0.001$) (Figure 2.6. B). Unlike in this study, several studies reported strong associations between NDVI and CC N content. White et al. (2019) found that there was a strong exponential relationship with GreenSeeker NDVI and CC N content ($0.72 < R^2 < 0.87$). Moreover, they developed models for different CC management strategies, *i.e.*, monoculture or mixtures, mixtures of grasses, mixtures of legumes, mixtures of brassicas, and even mixtures of different CC types. Yuan et al. (2019) reported a strong correlation between aerial imagery NDVI and CC N content ($0.77 < R^2 < 0.86$). As mentioned before this could be attributed to the low CC biomass production which reduced saturation issue that is commonly associated with NDVI. Chlorophyll and biomass yield in crops increased with N rates potentially lowering spectral reflectance in the visible light range; but changes in canopy spectral reflectance were not stable. Reflectance readings at early growth and senescence period was more constant because of the uncovered soil and senesced leaves. However, full green canopy
coverage showed no difference in reflectance (Li et al., 2018). This can explain the saturation effect that limits NDVI readings when cover crops are fully developed before termination.

Figure 2.6. Relationships between GreenSeeker (A) and aerial imagery (B) NDVI and CC dry biomass nitrogen content, 2020 and 2021. Sugar Research Station in St. Gabriel, LA.

The NDVI readings collected from the multispectral camera encountered issues on saturation more than the GreenSeeker sensor did, especially when the crop was greener
and the canopy was fully grown (Forestieri, 2021). As show in Figure 2.6, similar results were obtained in this study, where GreenSeeker was able to explain more of the CC N content variability than the multispectral camera.

Lelong et al. (2008) indicated that there was a better relationship of green-NDVI (GNDVI) than NDVI, computed from the reflectance at red band (570 – 650 nm), with N content in the plant and that the NDVI was better related to leaf area index (LAI), thus to biomass. Even so the study conducted by Yuan et al. (2019) showed that otherwise, i.e., GNDVI had lower correlations with CC biomass N content compared with NDVI (0.22<R²<0.89). Similar findings were reported by Caturegli et al. (2016) showing higher linear correlation of GreenSeeker NDVI with turfgrasses N content than aerial imagery NDVI. They also pointed out that a ground-sensor is sufficient to use for a relatively small area, however the NDVI derived from aerial imagery is more appropriate for large areas assessment of N status and spatial variability.

2.3.7. Linear regression between macronutrients content in cover crop biomass and normalized difference vegetation index (NDVI) derived from both sensors

Table 2.6 provide the intercepts, slopes, and R² of the linear relationship between NDVI readings and macronutrient content in CC biomass. The R² values obtained ranged from 0.12 to 0.48 for the GreenSeeker NDVI and from 0.001 to 0.23 for the aerial imagery NDVI.

For phosphorus (P), 36% and 13 % of the variation of the P content of CC biomass could be explained by GreenSeeker NDVI and aerial imagery NDVI respectively. While the correlations are relatively weak, the regression analysis was statistically significant, suggesting that P content is linearly related to the NDVI measurements from both
sensors. Several studies pursued the use of NDVI on P monitoring in plants. The correlations of NDVI derived from a spectroradiometer and a multispectral camera mounted on a UAV against leaf P content were weak within P fertilization levels but the correlations improved when leaf P from all P levels were included yielding R² values of 0.45 and 0.64 for each sensor, respectively (Gracia-Romero et al., 2017). Sembiring et al. (1998) identified indices W705/545 (R²=0.45) and W725/655 (R²=0.46) as potential predictors of P uptake by wheat. Moreover, they noted that NDVI was also a good index to predict P uptake (p-value <0.01). Contrary to these studies, no association among the aboveground biomass of mixed grasses, plant P content and NDVI from satellite imagery was documented by Gopp et al., (2019). Mahajan et al. (2014) also noted that NDVI and other VIs from spectrometer readings were not able to predict P concentration in wheat. Later Mahajan et al. (2017) revealed the poor predictive ability of various VIs (including NDVI) for P content in rice (Oryza sativa).

Among the nutrients taken up by CC, potassium (K) obtained the highest association with GreenSeeker NDVI and aerial imagery NDVI among the nutrients with R² values of 0.48 and 0.23, respectively even surpassing N (p<0.001). Guo et al. (2017) obtained a correlation coefficient (r) between NDVI (749 nm and 1215 nm) and K content in apple (Malus domestica) leaves of 0.43 (R²=0.19). Moreover, they indicated that reflectivity would increase with a rise on K leaf content, especially in wavelengths at visible light 350 - 680, NIR 800 - 1300, 1400 - 1850, and 1900 – 2500 nm. Mahajan et al. (2014) obtained a small correlation (R²=0.08, p<0.05) between spectrometer derived NDVI and K content in wheat. Estimation with very good accuracy (R²>0.8) of K concentration of turfgrasses,
perennial ryegrass (*Lolium perenne* L.) and bermudagrass (*Cynodon dactylon* L.), were found using the NDVI derived from a GreenSeeker hand-held meter (Sekerli et al., 2021).

The relationships of sulfur (S) content in CC biomass with GreenSeeker and aerial imagery NDVI were both weak with $R^2$ values of only 15% and 2%, respectively ($p<0.05$). Both regression models were significant ($p<0.05$) but very weak in terms of explaining the viability in S content of CC biomass. Similar outcomes were reported from previous studies. Mahajan et al. (2014) reported that the regression model for NDVI gathered with an analytical spectral device field spectrometer and S content on wheat was significant ($p<0.05$) but with a very low $R^2$ (0.096). The NDVI was among the six VIs that were evaluated for prediction of S concentration in rice leaves but also yielded low $R^2$ (0.096) (Mahajan et al., 2017).

The current study demonstrated that both GreenSeeker and aerial imagery NDVI had weak to virtually no correlation with calcium (Ca) content in CC biomass. The GreenSeeker NDVI linear regression model was significant ($p<0.001$) but can explain only 12% variability in Ca content in CC biomass. On the other hand, a non-significant result was obtained for the linear model between aerial imagery NDVI and Ca content thus aerial imagery NDVI cannot be used to predict Ca content in CC biomass. Coelho et al. (2021) explained that the lack of relation between the maximum Ca content in leaves of potato (*Solanum tuberosum*) and UAV derived NDVI was possibly due to the overriding effect of Ca toxicity in the field. As it turned out positively, the NDVI map was then used to highlight this nutritional problem in the field.

The linear regression models for GreenSeeker NDVI and aerial imagery NDVI with magnesium (Mg) content in CC biomass were both significant ($p<0.001$) but can only
account 24% and 13% variability in Mg content in CC biomass, respectively. Similarly, Gopp et al. (2020) found a positive correlation between Mg content in biomass with satellite derived NDVI, being NDVI able to explain 26% of the variance of the total content of Mg in a mixture of oat (Avena sativa L.) and pea (Pisum sativum L.) plant tissue.

Table 2.6. The components and coefficient of determination (R²) of the linear relationships of GreenSeeker and aerial imagery NDVI with macronutrients content in cover crop biomass, 2020 and 2021, Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Nutrient</th>
<th>GreenSeeker</th>
<th>Aerial Imagery</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept</td>
<td>Slope</td>
</tr>
<tr>
<td>P</td>
<td>-0.39</td>
<td>6.56</td>
</tr>
<tr>
<td>K</td>
<td>-4.34</td>
<td>46.32</td>
</tr>
<tr>
<td>S</td>
<td>0.38</td>
<td>4.83</td>
</tr>
<tr>
<td>Ca</td>
<td>0.96</td>
<td>20.97</td>
</tr>
<tr>
<td>Mg</td>
<td>-1.73</td>
<td>12.62</td>
</tr>
</tbody>
</table>

*** p<0.001
* p<0.05
NS p>0.1

2.3.8. Linear regression between micronutrients content in cover crop biomass and normalized difference vegetation index (NDVI) derived from both sensors

Micronutrients content in CC biomass regression with NDVI values analysis intercepts, slopes, and R² are shown in Table 2.7. The linear regression models for boron (B), copper (Cu), manganese (Mn), molybdenum (Mo), and nickel (Ni) content in CC biomass and NDVI from both sensors were significant (p<0.001). The R² values varied among the linear models but in all cases GreenSeeker NDVI had higher R² values for Mn, Cu, B, Mo, and Ni content in CC biomass at 0.41, 0.38, 0.32, 0.3, and 0.19 compared to 0.23, 0.12, 0.09, 0.09 and 0.03 of the aerial imagery NDVI, respectively.
Despite the recognized function of zinc (Zn) and iron (Fe) on chlorophyll biosynthesis, the relationship of NDVI with Zn and Fe content in CC biomass was generally weak. Zinc and Fe had the lowest $R^2$ values among the nutrients with 0.13 and 0.07 for GreenSeeker NDVI and 0.0006 and 0.001 for aerial imagery NDVI, respectively. Additionally, a difference between the significance of the statistical test obtained for both sensors. For the GreenSeeker NDVI the linear model was significant ($p<0.001$) for both Fe and Zn. However, the regression model for aerial imagery NDVI and Zn or Fe content was neither significant. Pandey et al. (2017) mentioned that in general micronutrients were modeled with less precision than macronutrients using a hyperspectral imaging system in corn (Zea mays) and soybeans (Glycine max). They reported that the highest correlation with Cu and Zn with validation $R^2$ of 0.86 and 0.73, followed by Fe and Mn with $R^2$ of 0.68 and 0.64, ending with Na and B as the lowest with validation $R^2$ of 0.29 and 0.18, respectively. They pointed out that nutrients that cause distinct visual deficiency symptoms, as chlorosis or necrosis, will be easily captured. Prananto et al. (2020) indicated that due to their low quantities in plant tissues and the lack of spectral fingerprints, near infrared spectroscopy (NIRS) is less reliable in assessing micronutrients. Nevertheless, they found good correlations for micronutrients Fe, Zn, Mn, and Cu with $R^2$ of 0.81, 0.67, 0.41, and 0.52, correspondingly. Good prediction accuracy was obtained for Cu and Fe ($R^2=0.72$ & 0.57) followed by a lower performance for Zn and Mn ($R^2=0.43$ & 0.03) using a hand-held GreenSeeker on turfgrass (Sekerli et al., 2021).

Manganese and Cu obtained the highest $R^2$ in this study. Pandey et al. (2017) and Sekerli et al. (2021) described Cu as the micronutrient associated with reflectance readings taken with similar waveband used in this study to compute NDVI. In contrast, both of these
Table 2.7. The components and coefficient of determination ($R^2$) of the linear relationship of GreenSeeker and aerial imagery NDVI with micronutrients content in cover crop biomass, 2020 and 2021, Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Nutrient</th>
<th>GreenSeeker</th>
<th>Aerial Imagery</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept</td>
<td>Slope</td>
</tr>
<tr>
<td>B</td>
<td>-0.0045</td>
<td>0.04</td>
</tr>
<tr>
<td>Cu</td>
<td>-0.0009</td>
<td>0.016</td>
</tr>
<tr>
<td>Fe</td>
<td>0.41</td>
<td>1.50</td>
</tr>
<tr>
<td>Mn</td>
<td>-0.002</td>
<td>0.16</td>
</tr>
<tr>
<td>Mo</td>
<td>-0.0006</td>
<td>0.005</td>
</tr>
<tr>
<td>Ni</td>
<td>0.0009</td>
<td>0.005</td>
</tr>
<tr>
<td>Zn</td>
<td>0.01</td>
<td>0.06</td>
</tr>
</tbody>
</table>

*** $p<0.001$
** $p<0.01$
NS $p>0.1$

authors and Prananto et al. (2020) indicated Mn having the lowest $R^2$ with NDVI. Iron and Zn were lowest in terms of percentage of variability captured by both sensors used in this study. In contrast to Pandey et al. (2017) and Sekerli et al. (2021), both nutrients were the second and third highly correlated with NDVI, which is quite similar to the report by Prananto et al. (2020) wherein Fe having the highest correlation with NDVI. These differences can be attributed to the difference in sensing tools and techniques such that other used more sensitive sensors i.e., spectrometers, and sensing position i.e., above the canopy in a nadir position versus whole plant from the side. While the B concentration in CC biomass was evidently lower than many micronutrients such as Fe, the NDVI obtained a relatively good correlation with B uptake by CC. This was in contrary to the results from previous studies (Pandey et al., 2017; Prananto et al., 2020; Sekerli et al., 2021). NDVI is a good predictor of B uptake because, it is computed as the product of biomass and then related to B concentration.
2.3.9. Converting aerial imagery NDVI into GreenSeeker NDVI to improve relationships.

Considering that GreenSeeker NDVI performed better than aerial imagery NDVI and the strong relationship between NDVI derived from both sensors have, it is possible to use the relation to convert aerial imagery NDVI into GreenSeeker NDVI and then use the equation for dry biomass and nutrient content estimation.

The linear relation between GreenSeeker NDVI and aerial imagery NDVI is showed in Figure 2.4 A. The equation is:

\[ NDVI - AI = 0.191 + 0.726 \times NDVI - GS \quad \text{Eq. 2.1} \]

From Eq. 2.1, we can obtain GreenSeeker NDVI using aerial imagery NDVI, as follows:

\[ NDVI - GS = \frac{NDVI - AI - 0.191}{0.726} \quad \text{Eq. 2.2} \]

Then we can use the linear relationship of GreenSeeker NDVI and CC dry biomass, showed in Figure 2.5 A:

\[ CC \text{ Dry biomass (kg ha}^{-1}\text{)} = 188 + 2.54 \times 10^3 \times NDVI - GS \quad \text{Eq. 2.3} \]

Incorporating Eq. 2.2 into Eq. 2.3, as resulting improved relationship for aerial imagery NDVI:

\[ CC \text{ Dry biomass (kg ha}^{-1}\text{)} = 188 + 2.54 \times 10^3 \times \frac{NDVI - AI - 0.191}{0.726} \quad \text{Eq. 2.4} \]

The same approach can be employed using adjusted NDVI between both sensors. Adjusted NDVI with ND, CGDD and NP-GDD relationships are showed in Figure 2.4 B, C and D, as follows:
\[
\frac{NDVI - AI}{ND} = 0.000906 + 0.919 \times \frac{NDVI - GS}{ND}
\]
Eq. 2.5 (Adjusted with ND)

\[
\frac{NDVI - AI}{CGDD} = 8.57 \times 10^{-5} + 0.948 \times \frac{NDVI - GS}{CGDD}
\]
Eq. 2.6 (Adjusted with CGDD)

\[
\frac{NDVI - AI}{NP-GDD} = 0.00104 + 0.885 \times \frac{NDVI - GS}{NP-GDD}
\]
Eq. 2.7 (Adjusted with NP-GDD)

Solving Eq. 2.5, 2.6 and 2.7 for GreenSeeker NDVI:

\[
NDVI - GS = \frac{NDVI - AI - (0.000906 \times ND)}{0.919}
\]
Eq. 2.8

\[
NDVI - GS = \frac{NDVI - AI - (8.57 \times 10^{-5} \times CGDD)}{0.948}
\]
Eq. 2.9

\[
NDVI - GS = \frac{NDVI - AI - (0.00104 \times NP-GDD)}{0.885}
\]
Eq. 2.10

Similar procedure as Eq 2.4 can be done incorporating Eq. 2.8, 2.9, and 2.10 into Eq. 2.3, improving the relationship for aerial imagery NDVI:

\[
CC \ Dry \ biomass \ (kg \ ha^{-1}) = 188 + 2.54 \times 10^3 \times \frac{NDVI - AI - (0.000906 \times ND)}{0.919}
\]
Eq. 2.11

\[
CC \ Dry \ biomass \ (kg \ ha^{-1}) = 188 + 2.54 \times 10^3 \times \frac{NDVI - AI - (8.57 \times 10^{-5} \times CGDD)}{0.948}
\]
Eq. 2.12

\[
CC \ Dry \ biomass \ (kg \ ha^{-1}) = 188 + 2.54 \times 10^3 \times \frac{NDVI - AI - (0.00104 \times NP-GDD)}{0.885}
\]
Eq. 2.13

The same approach can be done for nutrient content, especially for those nutrients with high R². However, more research must be done testing these model that presumably can help to establish better future estimations, using a passive sensor. This framework is just a theoretical conceptualization. Nevertheless, this exemplifies the usefulness of both sensors, improving the relation of one by using the other sensor’s relationship.
2.4. CONCLUSIONS

This study showed strong linear relationship between GreenSeeker NDVI and aerial imagery NDVI. The regression model was significant and was able to explain more than 60% of the variability in aerial imagery NDVI. The adjustment of NDVI with CGDD ND and NP-GDD from planting to sensing dates improved the linear relationship between the two sensors.

The GreenSeeker NDVI performed better than aerial imagery NDVI in terms of explaining variation in CC dry biomass yield and nutrient content. This can be explained by environmental aspects, like humidity, wind, distance above the canopy that easily alters the performance of passive sensor compared to the active sensor. Furthermore, saturation for both sensors became an apparent issue when biomass was high (<2000 kg ha\(^{-1}\)) or where there was complete coverage of the soil (background). However, the active sensor was less affected by saturation than the multispectral camera.

The stronger relationships for macronutrients found in this study were for N, K and P, followed by Mg and low values for S and Ca. For micronutrients the stronger relationships were found for Mn and Cu, followed by Mo and Ni, and low relationship for Fe and Zn.

A framework was introduced to convert aerial imagery sensing data into GreenSeeker readings, to obtain better estimations for aerial imagery. However, more research and test must be done to corroborate this concept. Finally, more research is needed to establish a model to predict CC biomass and nutrient content based on remote sensing data derived from different sensors.
CHAPTER 3. DETERMINE THE IMPACT OF PLANTING METHOD AND RATE OF COVER CROPS ON SOIL NUTRIENT LEVELS AND ON SUGARCANE YIELD AND QUALITY COMPONENTS

3.1. INTRODUCTION

Sugarcane (*Saccharum spp*) is a fast growing grass with a C4 photosynthetic pathway and a high biomass producing crop that can be harvested annually for several years without replanting (Meyer et al., 2011; Kaffka & Grantz, 2014). Generally, every 2 to 4 years sugarcane is planted. A second crop of stalks (ratoon) grows after the harvest of the first crop called plant cane (Schmitz et al., 2017). A year later the second crop is harvested. On average, one field is replanted after 3 annual crops are harvested (Baucum & Rice, 2009).

Sugar production is a key source of income in Louisiana (Schmitz et al., 2020). Sugarcane represent 27% of the total value of crop production in Louisiana in 2021 (USDA-NASS, 2022b). Sugarcane was grown on 200,829 hectares in Louisiana in 2020 with an average of 80.7 Mg ha\(^{-1}\) and 116.5 kg of sugar per Mg of cane (Gravois, 2021).

Sugarcane fields in Louisiana are commonly replanted every four years, mostly because to declining yields and the costly process. This cycle is necessary and an opportunity to maximize the economic benefits during the next four-year cropping cycle (Webber III et al., 2016). Sugarcane production is considered under a monoculture system, a farming systems where a single crop is grown uninterrupted, without or with short fallow periods (Schumann et al., 2000). Under these circumstances, sugarcane fields are subject to soil degradation and decline in terms of productivity potential.
The fertilizer requirement of sugarcane differs between crop age wherein lower rates of nitrogen (N), phosphorus (P) and potassium (K) are recommended for plant cane than ratoon crops (Santos et al., 2015). Nitrogen rates for sugarcane in Louisiana are between 67-112 kg ha\(^{-1}\) for plant cane and between 90-135 kg ha\(^{-1}\) for ratoon. Phosphate rate are between 45-56 kg ha\(^{-1}\) for plant cane and between 45-67 kg ha\(^{-1}\) for ratoon. Potash application are between 90-135 kg ha\(^{-1}\) for plant cane and between 90-157 kg ha\(^{-1}\) for ratoon (Gravois et al., 2014)

Implementation of practices that can improve or maintain the soil quality and soil health are necessary in sugarcane production. As a monoculture crop, the lack of diversity on soil biological activity can impose a detrimental effect on soil productivity (Dick, 1992). One of conservation practices is the introduction of cover crops (CC) in the system. In accordance with yield decline observed in monoculture system, a renewed interest in the practice of green manuring for sugarcane has risen (Schumann et al., 2000). One alternative is to plant CC few weeks after sugarcane seeding and terminating them at the end of winter or the beginning of spring. This is also known as intercropping. This practice showed that sugarcane productivity can be enhanced or maintained by improving on soil quality.

Inclusion of CC, improves soil health as compared to leaving soils fallow after harvesting the main crops (Wienhold et al., 2006). Cover crops play crucial roles in serving ecosystems through nutrient cycling (Coombs et al., 2017). Planting winter CC increased soil carbon © and retained inorganic N compared to fallow (Wright, Hons, & Rouquette, 2004; Hubbard, Strickland, & Phatak, 2013). Catch crops are CC that grow during the
fallow season to take up nutrients, that on the other hand would be lost if plants are not present (Hatfield & Sauer, 2011).

Sugarcane reaches full canopy closure between 3–5 months of growth, therefore, short-duration winter crops can be effectively cultivated between two cane rows' exposed soil surface areas (Rahman et al., 2016). As the new planted sugarcane develops, the idea is to cultivate a winter CC at the same time (Orgeron & Gravois, 2020). Cover crops have been studied as a rotating crop in the fallow season or as an intercrop in newly planted sugarcane in Louisiana sugarcane production systems (Forestieri, 2021). Scandaliaris et al. (2002) studied the use of CC in cane cultivation, CC lowered evaporation rates, provided a physical barrier to weed development, and improved soil quality in addition to lowering surface erosion. Platford (1987) estimated that 85-90 percent of soil loss in sugarcane fields happens during replanting.

Cover cropping effects varied, but on average, resulted in the production of sugarcane stalks with higher sucrose content but of similar tonnage, when compared to the sugarcane following a fallow (White et al., 2020). Herbert & Davidson (1959) mentioned when cane trash and legumes were integrated into the soil, both cane and sucrose yields increased on both well drained light silt loam and poorly drained silt loam soils however, the same treatments had no effect on yields for cane grown on poorly drained silty clay soil. The findings revealed that even when green manures were used, inorganic fertilizer was still required for profitable cane production such that the addition of both green manure and fertilizer N resulted in yields higher than when fertilizer N was applied alone (Prammanee et al., 1996; Schumann et al., 2000).
Fixation of large amounts of N may be problematic if uncontrolled mineralization under warm and wet conditions takes place as this can lead to large nitrate (NO$_3^-$)-leaching losses in the weeks or months after the CC are terminated (Di Bella et al., 2021). Legume CC sown over the winters when sugarcane is in the ground can supply more than 112 kg of N per hectare (Gravois et al., 2011).

Unfortunately, one of the drawbacks of increasing CC planting is the lack of available time, as a result, farmers want to use a faster method for sowing CC that will allow them to cover more area during a time of year when time, daylight, favorable weather, and manpower are all limited (Fisher et al., 2011). The time and type of planting are both important factors in the successful establishment of CC (Noland et al., 2018).

Broadcasted seeds performs different than drilled seeds because seed are under different environmental conditions, affecting germination and production (Koehler-Cole & Elmore, 2020). Planting by broadcasting involves less labor, is potentially less expensive, and can free up time for other activities (Wilson et al., 2014; Koehler-Cole & Elmore, 2020). Drilling seed rather than broadcasting was a more successful method for establishing CC because seed-to-soil contact was better (Fisher et al., 2011; Haramoto, 2019). When interseeding CC, new planting methods have been created to distribute seed directly in the inter-row and maximize seed-to-soil contact (Noland et al., 2018). Cover crops should be put in the wheel furrow and along the sides of the row rather than on the top of the row because sugarcane output is greatly reduced by CC sown on the row top of newly planted sugarcane (Orgeron & Gravois, 2020).

The quantity of biomass desired or the cost of seeds can be used to estimate seeding rates (Haramoto, 2019). Nevertheless, compensatory effect has been reported, where
seeding rate had no effect on aboveground dry matter accumulation (Boyd et al., 2009; Haramoto, 2019). Increasing seeding rates increases fall plant population but did affect spring CC biomass production (Koehler-Cole & Elmore, 2020). However, Brennan & Boyd (2012) reported that total biomass increase with higher seeding rates in legume-rye mixtures of CC. Therefore, this study was established to determine the impact of planting method and seeding rate of CC on soil nutrients levels and on sugarcane yield and quality components.

3.2. MATERIALS AND METHODS

3.2.1. Site description, planting method, treatment structure and trial establishment

This research was established at five sites: two sites were conducted between September 2019 to November 2021 (plant cane and first ratoon) and the rest from August 2020 to November 2021 (only plant cane) at the LSU AgCenter Sugar Research Station in St. Gabriel, LA (Latitude 30°, 15’, 13” N; Longitude 91°, 06’, 05” W). Data on soil surveys was obtained via the Soil Survey Website from the Natural Resources Conservation Service (NRCS). Sites 1 and 3 are on fields with Commerce silt loam soil whereas sites 2, 4 and 5 are on fields with a mixture of Commerce silt loam and Commerce silty clay loam soils. These soils have a taxonomic classification of Fine-silty, mixed, superactive, nonacid, thermic Fluvaquentic Endoaquepts (Soil Survey Staff, 2021). These are flood plain Inceptisols, poorly drained, saturated for some time of the year, with high-water table (Soil Survey Staff, 2015). Table 3.2 shows the initial soil properties and nutrient concentration of each site.
All sites were planted with sugarcane variety L 01-299. This variety is one of the most predominant varieties in Louisiana. It was derived from the cross made between L 93-365 as the female parent and LCP 85-384 as the male parent (Gravois et al., 2011).

Soil was mechanically disked, with approximately 1.2 m wide beds and 0.3 m height. Sugarcane stalks between 1.2 and 1.7 m of length were cut with a whole stalk harvester and loaded to a tractor wagon. Stalks were planted by hand placing four stalks side by side into an open furrow with approximately 10 cm overlapping ends. The furrows were covered with soil and compacted with a custom roller packer. All sites established 1.5 m (5 ft) alley gaps (with no stalks) to separate treatment plots.

The treatment structure was composed by eight combinations of different CC planting methods (broadcast and drilling) and seeding rates (100%, 50%, 25%, and 0 of the recommended rate by Natural Resource Conservation Services or NRCS). The treatment structure is presented in detailed in Table 3.1. Each treatment was replicated four times in each site. The treatments at site 1 were arranged in a completely randomized design (CRD) with treatment plots of 12 m (40 ft) long and 5.5 m (18 ft) (3-row) wide.

Table 3.1. Treatment structure of the study established at the LSU AgCenter Sugar Research Station in St. Gabriel, LA

<table>
<thead>
<tr>
<th>Treatment Number</th>
<th>Planting Method</th>
<th>Seeding Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Broadcast</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Broadcast</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>Broadcast</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>Broadcast</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>Drilling</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>Drilling</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>Drilling</td>
<td>50</td>
</tr>
<tr>
<td>8</td>
<td>Drilling</td>
<td>25</td>
</tr>
</tbody>
</table>
Table 3.2. Initial characterization of the soils in the experimental sites, 2019 to 2021, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Depth</th>
<th>pH*</th>
<th>Organic Matter†</th>
<th>Ammonium-N‡</th>
<th>Nitrate-N‡</th>
<th>Phosphorus§</th>
<th>Potassium§</th>
<th>Sulfur§</th>
<th>Calcium§</th>
<th>Magnesium§</th>
<th>Copper§</th>
<th>Zinc§</th>
<th>Sodium§</th>
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<tr>
<td>1:1 Water</td>
<td>%</td>
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<tr>
<td>0-15</td>
<td>5.6</td>
<td>1.7</td>
<td>21.1</td>
<td>10.9</td>
<td>40.9</td>
<td>188</td>
<td>20.5</td>
<td>2,029</td>
<td>440</td>
<td>3.4</td>
<td>3.0</td>
<td>51.3</td>
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<tr>
<td>Site 1 - Commerce silt loam</td>
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<tr>
<td>0-15</td>
<td>5.5</td>
<td>1.6</td>
<td>7.9</td>
<td>10.6</td>
<td>35.6</td>
<td>190</td>
<td>14.7</td>
<td>2,038</td>
<td>475</td>
<td>3.6</td>
<td>2.9</td>
<td>41.2</td>
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<td>Site 2 - Commerce silt loam &amp; Commerce silty clay loam</td>
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<tr>
<td>0-15</td>
<td>6.4</td>
<td>1.3</td>
<td>6.6</td>
<td>19.9</td>
<td>18.9</td>
<td>116</td>
<td>10.8</td>
<td>1,535</td>
<td>303</td>
<td>2.5</td>
<td>1.8</td>
<td>53.0</td>
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<td>Site 3 - Commerce silt loam</td>
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<tr>
<td>0-15</td>
<td>6.3</td>
<td>1.2</td>
<td>5.6</td>
<td>11.0</td>
<td>16.1</td>
<td>109</td>
<td>8.2</td>
<td>1,575</td>
<td>310</td>
<td>2.7</td>
<td>1.8</td>
<td>56.0</td>
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<td>Site 4 - Commerce silt loam &amp; Commerce silty clay loam</td>
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<tr>
<td>0-15</td>
<td>5.8</td>
<td>1.3</td>
<td>7.4</td>
<td>9.5</td>
<td>22.6</td>
<td>176</td>
<td>8.0</td>
<td>2,034</td>
<td>465</td>
<td>3.3</td>
<td>2.1</td>
<td>65.1</td>
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<tr>
<td>Site 5 - Commerce silt loam &amp; Commerce silty clay loam</td>
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</tr>
<tr>
<td>0-15</td>
<td>5.8</td>
<td>1.9</td>
<td>9.9</td>
<td>18.7</td>
<td>32.2</td>
<td>226</td>
<td>10.9</td>
<td>2,467</td>
<td>572</td>
<td>4.5</td>
<td>3.2</td>
<td>60.6</td>
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</tr>
<tr>
<td>15-30</td>
<td>6.3</td>
<td>1.5</td>
<td>4.9</td>
<td>7.3</td>
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<td>221</td>
<td>6.9</td>
<td>2,957</td>
<td>673</td>
<td>5.4</td>
<td>2.9</td>
<td>75.4</td>
</tr>
</tbody>
</table>

* 1:1 w/v soil: deionized water ratio (McLean, 1982)
† Acid-dichromate oxidation (Nelson and Sommer, 1982)
‡ Based on Mehlich 3 procedure (Mehlich, 1984)
§ Based on 1M KCl extraction procedure followed by Flow Injection Analysis (FIA)
Treatments at sites 2 to 5 were laid-out in a randomized block design (RBD) with plot size of 15 m (50 ft) long and 5.5 m wide.

For this study five CC species were planted in a mix, a month after sugarcane was planted. Three were legumes, hairy vetch (*Vicia villosa*), crimson clover (*Trifolium incarnatum*) and balansa clover (*Trifolium balansae*). The other two species were brassicas, tillage radish (*Raphanus sativus var. niger*) and rapeseed (*Brassica rapa*). Cover crops seeding rates for each site are presented in Table 3.3.

Table 3.3. Cover crop species and seeding rates planted for the different treatments (planting method and NRCS rates) per site, 2019 and 2020, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Planting method</th>
<th>Seeding rate</th>
<th>Crimson clover</th>
<th>Balansa clover</th>
<th>Hairy vetch</th>
<th>Tillage radish</th>
<th>Rapeseed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1-2</td>
<td>2019</td>
<td>Broadcast</td>
<td>100%</td>
<td>11.21</td>
<td>5.60</td>
<td>13.45</td>
<td>2.24</td>
<td>2.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>5.60</td>
<td>2.80</td>
<td>6.73</td>
<td>1.12</td>
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<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>2.80</td>
<td>1.40</td>
<td>3.36</td>
<td>0.56</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Drilling</td>
<td>100%</td>
<td>6.73</td>
<td>4.48</td>
<td>8.97</td>
<td>1.12</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>3.36</td>
<td>2.24</td>
<td>4.48</td>
<td>0.56</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>1.68</td>
<td>1.12</td>
<td>2.24</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Site 3-4-5</td>
<td>2020</td>
<td>Broadcast</td>
<td>100%</td>
<td>8.56</td>
<td>19.84</td>
<td>13.45</td>
<td>2.27</td>
<td>2.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>4.28</td>
<td>9.92</td>
<td>6.73</td>
<td>1.13</td>
<td>1.12</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>2.14</td>
<td>4.96</td>
<td>3.36</td>
<td>0.57</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Drilling</td>
<td>100%</td>
<td>6.84</td>
<td>11.90</td>
<td>8.97</td>
<td>1.13</td>
<td>1.12</td>
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<td></td>
<td></td>
<td></td>
<td>50%</td>
<td>3.42</td>
<td>5.95</td>
<td>4.48</td>
<td>0.57</td>
<td>0.56</td>
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<td></td>
<td></td>
<td></td>
<td>25%</td>
<td>1.71</td>
<td>2.98</td>
<td>2.24</td>
<td>0.28</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Note: 100% seeding rates for all the cover crops species are based on NRCS recommendation.

### 3.2.2. Soil sampling

Soil sampling were done at the termination of the CC, during midseason, and after sugarcane harvest for each site. Soil samples were collected at two depths, 0 – 15 and 15 – 30 cm. Samples were taken using a standard soil probe with footstep (JMC). Soil
samples were made out of sixteen cores per plot and combined. Samples were placed in labeled paper bags. Samples were oven-dried using a Despatch LBB series oven (model number LBB2-18-1) for a minimum of three days (72 hours) at 60°C. The samples were then ground, with a Humboldt electric flail grinder and sieved through a built-in 2 mm sieve and placed in labeled plastic bags.

### 3.2.3. Soil analysis

Determination of inorganic N content was done by KCl extraction procedure for ammonium (NH$_4^+$) and nitrate (NO$_3^-$). Five grams of dried soil were weighed and placed inside a 125 ml plastic bottle. Then each plastic bottle was dispensed with 35 ml of 1 M KCl. Soils samples were then shaken for 1 hour on reciprocal shaker at high speed. The soil suspension was then filtered using No. 42 Whatman® filter paper. After filtering, the samples extracts were frozen and thawed prior to flow injection analysis (FIA). Determination of NH$_4^+$ and NO$_3^-$ concentration in sample extracts was completed through colorimetric using a FIA Lachat QuickChem 8500 series 2. Similar FIA procedures like those presented on López Pasquali et al., (2007), for inorganic N were used. Nitrate-N was quantified by the reduction of NO$_3^-$ to NO$_2^-$ when passing through a copper cadmium reduction column and then reacting with the coloring reagent sulfanilamide to produce a reddish pink color under the acidic condition that can be quantified through colorimetric analysis at 520 nm (Keeney & Nelson., 1982). Ammonium-N was determined based on the salicylate method (Reardon et al., 1966), wherein sample extract is heated with salicylate and hypochlorite in an alkaline phosphate buffer environment resulting in formation of a blue-green color clear solution. The color is intensified by adding sodium nitroprusside with concentration measured by colorimetric analysis at 660 nm.
To determine the other soil nutrients content, a Mehlich-3 (Mehlich, 1984) extraction was carried out. Two grams of dried soil were weighed and placed inside a 125 ml plastic bottle. Then each plastic bottle was added with 20 ml of Mehlich-3 solution using a dispensing bottle. Samples were shaken on a reciprocal shaker at high speed for 5 minutes. The soil suspension was then filtered using size No. 2 Whatman® filter paper. After filtering, samples extracts were stored in the refrigerator. Samples were kept refrigerated until they were poured into 10 ml tubes and analyzed for macro and micronutrient concentrations using inductively coupled plasma (ICP).

3.2.4. Cane tonnage, Sugar yield and Quality Components

Stalk weight of all rows within plots was determined. A single-row chopper harvester (CASE IH Austoft® 8000 series cane harvester) was used to cut stalks from the base and chop into billets later to determine the millable stalk yield. Cut stalks were dispensed into a modified single axle high dump billet wagon using a built-in conveyor in the chopper harvester (Cameco Industries, Thibodaux, LA) and weighed via the electronic load sensor cells fitted in the wagon. Plot yield was used to estimate cane tonnage in Mg per ha. Before harvesting the middle row of each plot, ten random plants were harvested by hand, cleaned (leaves were taken off from the stalk), and tops were removed at approximately 10 cm below the apical meristem. The weight of the ten stalks was added to the total plot yield. The 10-stalk weights were used to establish average stalk weight.

The quality parameters were determined from the stalk samples. The stalk samples were shredded and analyzed by SpectraCane automated near infrared (NIR) analyzer (Bruker Corporation, Billerica, Massachusetts). Results of analysis included parameters such as:
theoretical recoverable sugars (TRS), Brix, sucrose, purity, polarity, moisture, and fiber. Sugar yield (kg ha\(^{-1}\)) was computed as the product of cane yield and TRS.

The TRS is the total concentration of sugars (sucrose, glucose, and fructose) recovered in the industrial process. From there sucrose, represent a fraction of the TRS. Brix is the total dissolved solids in sugar liquor or syrup determined using a refractometer expressed as percentage by mass (Meyer et al., 2011). Moreover, polarity is the apparent sucrose content expressed as a mass percent measured by the optical rotation of polarized light passing through a sugar solution.

### 3.2.5. Data analysis

Statistical analyses were performed with the use of R project (R Core Team, 2022) through the integrated development environment (IDE) R Studio. Analysis of variance (ANOVA) was run through the corresponding function in native R. Least-square means were obtained using the “emmeans” package for R (Lenth, 2021). Planting method and seeding rates were treated as fixed effects in each site, for cane yield and quality parameters, as well as for soil nutrient concentration. Moreover, treatment effect on soil nutrient content were evaluated separately for each sampling time and depth.

### 3.3. RESULTS AND DISCUSSION

#### 3.3.1. Climatic conditions

The total monthly precipitation and average monthly temperature for the LSU AgCenter Sugar Research Station in St. Gabriel, LA obtained from the Baton Rouge Metro Airport weather station across crop years are reported in Figures 3.1 and 3.2, respectively. Sugarcane grows best at temperatures between 30-33°C while its development is compromised below 16°C (Bakker, 1999). Temperatures of 17.2 to 22.2°C were shown
to be optimal for dry matter accumulation and stalk elongation in sugarcane (Hunsigi, 1993).

The total precipitation in the first year of experiments was 1329 mm (March to November), with the highest monthly precipitation of 252.3 mm in October (Figure 3.1). For the second year of experiments, the total precipitation was 1843 mm (March to December), with the highest monthly value of 336 in May.

For the first year of experiments, sugarcane was planted on September 2019 and harvested in November 2020. During the growing period, the lowest monthly average temperature was 17.6°C in November, and the highest was 28.7°C in August (Figure 3.2). For the second year of experiments, sugarcane was planted in August and harvested in December. The lowest temperature was 14.3°C in November of 2021 and the highest was 27.8°C in July 2021.

Because of the mild February temperatures, the 2020 sugarcane crop had a good head start combined with rainfall that was average in terms of amount and distribution. All these provides practically optimal growing conditions (Gravois, 2021).
Figure 3.1. Monthly total precipitation (mm) from January to December in 2019, 2020, and 2021 at the LSU AgCenter Sugar Research Station in St. Gabriel, LA

Figure 3.2. Monthly average temperature (°C) from January to December in 2019, 2020, and 2021 at the LSU AgCenter Sugar Research Station in St. Gabriel, LA
3.3.2. Cover crop biomass proportion per specie

Cover crop dry biomass proportion per specie varied in all site-years (Figure 3.3). A total of 316 samples (1 m² each sample) of biomass were collected through all site-years. Cover crop dry biomass of each specie shows that the proportion did not vary greatly among the treatments where CC were planted. In all treatments native weeds were the more predominant specie (28-39%). Crimson clover obtained the higher ratio of biomass between CC in most treatments, ranging from 18 to 30%. This was followed by tillage radish with overall biomass between 19 to 28% in total, composed of dry leaves (6-16%) and roots (11-17%). Rapeseed followed ranging from 12 to 21% then hairy vetch with proportions of 1 up to 5%. Finally, balansa clover obtain the lowest biomass proportion, with values from 2 to 4%.

3.3.3. Impact of cover crops on sugarcane productivity and quality components

The results of the ANOVA for cane yield, sugar yield and quality components across sites are summarized in Tables 3.4 to 3.6. There was statistical difference on cane and sugar yield \((p\text{-value}=0.025)\) between planting method at site 5 (plant cane) (Table 3.5). Similarly, statistical differences were found at site 2 fist ratoon for quality parameters between different seeding rates; TRS, Brix and polarity \((p\text{-values}=0.035, 0.04, \text{ and } 0.041; \text{ respectively})\) (Table 3.6).
Figure 3.3 Cover crop dry biomass proportion per specie in each different planting methods and seeding rate at the Sugar Research Station in St. Gabriel, LA
Overall, no significant statistical difference was found for cane and sugar yield across sites between planting methods, apart from site 5 at plant cane (Tables 3.4, 3.5, and 3.6). Cane and sugar yield were numerically higher for broadcast planting method (107, 100 and 62 Mg ha\(^{-1}\) and 11630, 11572, and 6580 kg ha\(^{-1}\)) compared to drill seeding (104, 96 and 58 Mg ha\(^{-1}\) and 11087, 10997, 6186 kg ha\(^{-1}\)) at sites 1 and 5 plant cane and site 2 first ratoon. However, the opposite happened at sites 2 and 3 plant cane were drill seeding obtained higher values (92.3 and 91.9 Mg ha\(^{-1}\) and 10096 and 10996 kg ha\(^{-1}\)) compared to broadcast seeding (90.6 and 91.1 Mg ha\(^{-1}\) and 9856 and 10737 kg ha\(^{-1}\)). Furthermore, a different trend was found at site 4 plant cane and site 1 first ratoon. Higher cane yield was obtained from plots grown with broadcast-seeded CC (96 and 81.9 Mg ha\(^{-1}\)) compared to plots previously planted to drill-seeded CC (93.5 and 81.7 Mg ha\(^{-1}\)) but in terms of sugar yield higher level was recorded for the drill seed treatment (10485 and 8091 kg ha\(^{-1}\)) compared to the broadcast seed treatments (10482 and 7932 kg ha\(^{-1}\)).

No significant statistical difference was found for cane and sugar yield across sites between seeding rates. Additionally, no clear (increasing or decreasing) trend was found for the different seeding rates. It is worth noting that site 1 and 3 plant cane obtained the highest yield at the highest seeding rate. On the contrary, site 2 plant cane and site 1 first ratoon got the highest cane yield in the absence of CC.

There was no significant difference in TRS, Brix, sucrose, and polarity across sites between planting methods and seeding rates treatments, except for site 2 first ratoon for TRS, Brix and polarity, where higher values were found in the absence of CC and lower values for the highest seeding rate.
Table 3.4. Mean and analysis of variance on plant cane yield and quality components in 2020, under different cover cropping planting methods and seeding rates at the LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Source of variation</th>
<th>Cane yield</th>
<th>Sugar yield</th>
<th>TRS*</th>
<th>Brix</th>
<th>Sucrose</th>
<th>Polarity</th>
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</thead>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Mg ha⁻¹</td>
<td>kg ha⁻¹</td>
<td>kg Mg⁻¹</td>
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<td>%</td>
<td>%</td>
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<td>11087</td>
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</table>

* Theoretical recoverable sugar (TRS)
Table 3.5. Mean and analysis of variance on plant cane yield and quality components in 2021, under different cover cropping planting methods and seeding rates at the LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Source of variation</th>
<th>Cane yield Mg ha(^{-1})</th>
<th>Sugar yield kg ha(^{-1})</th>
<th>TRS* kg Mg(^{-1})</th>
<th>Brix</th>
<th>Sucrose</th>
<th>Polarity %</th>
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* Theoretical recoverable sugar (TRS)
Table 3.6. Mean and analysis of variance on first ratoon yield and quality components in 2021, under different cover cropping planting methods and seeding rates at the LSU AgCenter Sugar Research Station in St. Gabriel, LA.

<table>
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<tr>
<th>Location</th>
<th>Year</th>
<th>Source of variation</th>
<th>Cane yield</th>
<th>Sugar yield</th>
<th>TRS*</th>
<th>Brix</th>
<th>Sucrose</th>
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* Theoretical recoverable sugar (TRS)

Summer CC had no effect on sugarcane yield, which can be explained by the fact that after the first ratoon cane cycle, the effects of CC are minimized thereby reducing the differences whereas in cane plant it was attributed to soil tillage (Lovera et al., 2021). Similar findings were reported by White et al. (2020) showing that the establishment of summer CC during a typical fallow period had no significant impact on cane yield, despite the addition of nutrients from the CC. For cane and sugar yields, there were no significant
differences between the summer CC treatments and the control and there were no impact or benefit on TRS either (Webber III et al., 2016). On the other hand, Orgeron & Gravois (2020) reported an increase in cane yield, on plant cane, with the implementation of winter CC using a mixture of species compared to no-cover crops.

3.3.4. Impact of cover crops on plant available nutrients soil

The was no significant effect of planting method and seeding rate observed on soil NH$_4^+$ and NO$_3^-$ (Figures 3.3 and 3.4) and Mehlich-3 extractable nutrients (Figure 3.5 to 3.14) across sites and between the sampling depths, crop age, i.e., plant cane and first ratoon. In general, NO$_3^-$-N was the dominant form of inorganic N at termination and at harvest across sites (Figure 3.4). On the other hand, NH$_4^-$-N fraction was larger than NO$_3^-$-N at midseason sampling, mainly due to the recently released N from applied fertilizer. The levels of soil inorganic N were generally higher at the 0-15 cm than the 15-30 cm depth. The highest total inorganic N concentration was recorded at site 2, midseason averaging at about 75 mg kg$^{-1}$. Site 1 at midseason attained similar average as site 2 but this was recorded at the 15-30 cm depth indicating a possible movement of applied N from the surface. In 2020, rainfall between fertilization and soil sampling was of approximately a month apart, with 124 mm of precipitation recorded in May. For sites 3, 4, and 5, the inorganic N concentrations at midseason ranged from 20 to 40 mg kg$^{-1}$ (both depths); these were substantially lower than what obtained from at sites 1 and 2. Perhaps the differences in soil type, amount of rainfall, and sampling times (fertilization was done in May and soil sampling was done in August, with 482 mm of precipitation in between) may have contributed to this.
Legume CC are known to provide N to the subsequent cash crop through biological fixation. Yang et al. (2019) reported that mineralization of legume CC and soil organic matter provided sufficient N for subsequent corn (*Zea mays*) development, obtaining similar yields as conventional fertilization. However, even when legume CC can fix higher amounts of N, especially for hairy vetch, cash crop yield would be less or equal to 0 N applied (Parr et al., 2011). Moreover, CC can have an impact on retaining N that could have been lost. For example, the N in the legume CC biomass was linked with a reduction of 50 kg N ha⁻¹ in residual soil N in the soil profile (0–90 cm) compared the no-CC control treatment (Yang et al., 2019). Berseem clover (*Trifolium alexandrinum*), crimson clover (*Trifolium incarnatum* L.), hairy vetch (*Vicia villosa*), and Austrian winter peas (*Pisum sativum*) are widespread legume cover crops in Louisiana (Mite, 2020).
Figure 3.4. Soil NO$_3^-$-N and NH$_4^+$-N concentration at 0-30 cm depth at cover crop termination, midseason, and harvest of plant cane in 2020 (site 1 and 2) and 2021 (site 3, 4 and 5), at the LSU AgCenter Sugar Research Station in St. Gabriel, LA.
Despite the fact that brassica CC may quickly absorb huge amounts of N from the soil, they had either no effect or a negative effect on soil N at cash crop midseason (Northup & Rao, 2016). The use of radish as a cover crop to trap fall N is environmentally relevant because important levels of N were contained in plant biomass, although the fate of the N that is taken up remains unknown (Ruark et al., 2018). For this study, the flush of N from CC biomass was not recorded regardless of planting method and seeding rate. It is likely that the sampling time missed this particular period. Iamjud (2021) reported that optimum N degradation from CC biomass and availability to cash crop is between 4 to 6 weeks after CC termination. However, potentially mineralizable soil N was higher at 8 weeks after termination, suggesting that inorganic N was still released from CC residues.
Six weeks following the termination of the CC, the availability of soil NO$_3$-N peaked before declining in week eight (Iamjud & Fultz, 2020).

Phosphorous (P) concentration levels were generally constant across sampling times with, a slightly higher concentration at the 0-15 cm than the 15-30 cm depth. The highest P concentration was recorded at site 1, termination and midseason averaging at about 50 mg kg$^{-1}$. Sites 2 and 4 values did not change greatly through time. Site 3 obtained the lowest P concentration around 20 mg kg$^{-1}$. Site 5 and sites 1 and 2 first ratoon showed a decrease at midseason follow by a rise after sugarcane harvest.
Figure 3.6. Soil P concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of plant cane in 2020 (sites 1 and 2) and 2021 (sites 3, 4 and 5), LSU AgCenter Sugar Research Station in St. Gabriel, LA.
Figure 3.7. Soil P concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of first ratoon crop at sites 1 and 2 in 2021, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

Potassium (K) soil concentration levels did not vary across sampling times neither in depths. The highest K concentration was recorded at site 2, midseason averaging at about 210 mg kg\(^{-1}\), presumably caused by the K fertilization (89.7 kg of K\(_2\)O ha\(^{-1}\) done in all sites) followed by a decline at harvest. Similar trend was observed for site 1. For sites 3, 4, and 5, sites 1 and 2 first ratoon, no observable change in concentration was noted. However, there was a slight increase at harvest after midseason.
Figure 3.8. Soil K concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of plant cane in 2020 (sites 1 and 2) and 2021 (sites 3, 4 and 5), LSU AgCenter Sugar Research Station in St. Gabriel, LA.
In the case of sulfur (S) concentration levels were generally lower at midseason, more notably at 0-15 cm than the 15-30 cm depth. The highest S concentration was recorded at site 1 plant cane termination and same site first ratoon, averaging about 15 mg kg\(^{-1}\). Sites 2, 4 and 5, and sites 1 and 2 first ratoon values decrease after termination to midseason values and rise after midseason up to harvest values. Site 3 showed a constant increase in concentration from termination up to harvest.
Figure 3.10. Soil S concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of plant cane in 2020 (sites 1 and 2) and 2021 (sites 3, 4 and 5), LSU AgCenter Sugar Research Station in St. Gabriel, LA.
Figure 3.11. Soil S concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of first ratoon crop at sites 1 and 2 in 2021, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

Calcium (Ca) concentration levels were generally constant at different sampling times. The highest Ca concentration was recorded at site 5 termination averaging at about 3500 mg kg\(^{-1}\). Sites 1, 2 and 4, and sites 1 and 2 first ratoon concentrations averaged 2000 mg kg\(^{-1}\). Site 3 obtained the lowest Ca concentration between 1500 to 1800 mg kg\(^{-1}\).
Figure 3.12. Soil Ca concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of plant cane in 2020 (sites 1 and 2) and 2021 (sites 3, 4 and 5), LSU AgCenter Sugar Research Station in St. Gabriel, LA.
Figure 3.13. Soil Ca concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of first ratoon crop at sites 1 and 2 in 2021, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

Magnesium (Mg) soil concentration levels did not change greatly at different sampling times. The highest Mg concentration was recorded at site 5, termination averaging at about 850 mg kg$^{-1}$. Sites 1, 2 and 4, and sites 1 and 2 first ratoon concentrations averaged 500 mg kg$^{-1}$, a slight decrease was noticed between midseason and harvest, especially at 0-15 cm of depth. Site 3 obtained the lowest Mg concentration around 300 mg kg$^{-1}$. 
Figure 3.14. Soil Mg concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of plant cane in 2020 (sites 1 and 2) and 2021 (sites 3, 4 and 5), LSU AgCenter Sugar Research Station in St. Gabriel, LA.
Figure 3.15. Soil Mg concentration at 0-30 cm depth at cover crops termination, midseason, and harvest of first ratoon crop at sites 1 and 2 in 2021, LSU AgCenter Sugar Research Station in St. Gabriel, LA.

Forestieri (2021) reported that on Louisiana sugarcane production systems, CC affected positively soil extractable P, K, S, Ca, and Mg, with higher concentration in plots with CC than in plots without CC. For P, K, and S increments were observed within the first year after CC termination, however for soil Ca and Mg the effect was observed three years after CC termination.

Chu (2017) reported in a corn-soybean (Glycine max) cropping system that the adoption of multiple CC species exhibited statistically significant differences in K and Ca in a short-term trial under CC treatments compared to the control. Using mixed species of CC on a corn-soybean cropping system in Louisiana, Mite (2020) indicated that P, S and Mg
concentrations in the soil were stable through a 3-year period and without statistical difference with or without CC. However, for soil K higher values were recorded in plots with CC than in plots without CC after two years of CC practice. Soil Ca concentration was reduced after termination and later increased with time. The amount of nutrients stored in cover crop biomass does not result in a corresponding increase in nutrient levels in the soil, this will differ depending on the type of CC utilized (single or mixed), as well as soil types, weather conditions, and agricultural practices (Tubana et al., 2020).

3.4. CONCLUSIONS

This study demonstrated that a mix of legumes and brassicas winter CC can grow and develop good biomass under south Louisiana winter climatic conditions, planted as an intercrop in newly planted sugarcane.

Cane and sugar yield were not affected by winter CC planting methods and seeding rates. Planting methods and seeding rates did not impact any of the sugarcane quality components across site-years. However, two sites showed difference, one with higher yields for broadcasting CC and the second with higher quality components in the absence of CC.

Nutrient levels fluctuated throughout sites, years, crop age and sampling dates. However no statistical difference for nutrients concentrations were found for both planting methods neither for the different seeding rates. All this suggest that changes were caused by field conditions and nutrient uptake by sugarcane at sampling dates, rather than the imposed treatments.
The potential to improve soil health in sugarcane farming systems through the introduction of winter CC might be more visible in a longer term. In subsequent ratoons, a greater impact might be seen caused by the higher nutrient requirements by the older cane. Additionally, this study thus far corroborates the long-term effect of CC on nutrient management and their effect on cane yield and quality parameters. Future research should revolve on monitoring the effect on the complete sugarcane cycle, different mixes of CC, termination timing and different fertilization patterns.
CHAPTER 4. GENERAL CONCLUSIONS

The implementation of more sustainable management practices in sugarcane are required in Louisiana. Practices that improve soil health, like cool season cover crops (CC), need more understanding to facilitate successful and wide adoption. Moreover, remote sensing technologies can help us get more insights and spread the adoption of cover cropping. This research was initiated in 2019 at the LSU AgCenter Sugar Research Station in St. Gabriel, LA to evaluate the use of normalized difference vegetation index (NDVI) for cool season CC biomass and nutrient content; and to evaluate the impact of intercropping of cool season CC on sugarcane yield and quality component, and on soil nutrient content.

The outcome of the first study indicated a significant linear relationship between NDVI derived from GreenSeeker and aerial imagery with coefficient of determination ($R^2$) of 60%. Moreover, the linear relationship improved with the adjustment of NDVI with cumulative growing degree days (CGDD), number of days (ND), and number of days with positive GDD (NP-GDD) from planting to sensing dates. The GreenSeeker NDVI performed better than aerial imagery NDVI in terms of explaining the variation in CC dry biomass and nitrogen (N) content, mainly because of environment aspect that affect the nature of the reflectance data gather by each sensor. Furthermore, NDVI saturation problems were detected on both sensors, but with less influence on GreenSeeker, an active type of sensor.

The linear relationships between NDVI with potassium (K) and phosphorus (P) content in CC dry biomass obtained the highest $R^2$ values among the macronutrients. Manganese
(Mn) and copper (Cu) obtained the highest correlation values, among micronutrients, followed by Mo and Ni, which had fair linear relationships with NDVI.

The outcome of the second study showed that a mix of winter CC can be intercropped in newly planted sugarcane, obtaining good standings. No effect from planting methods and seeding rates were found on cane and sugar yield. Furthermore, no statistical difference was obtained on sugarcane quality parameters caused by the imposed treatments. Soil nutrient concentrations varied between sites, years, crop age, and sampling dates. Nevertheless, no significant impact was found on macronutrients concentrations by planting methods and seeding rates. These findings support the long-term effect of cover crops on nutrient management and their effect on cane yield and quality parameters.
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VITA

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