Achieving sustainable improvements in nutrient efficiency with precision agriculture

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Abstract
With the global population expected to surpass 9 billion people by 2050, sustainable increases in food production will be a necessity. A key contributor to this increase will be the use of mineral fertiliser. 4R nutrient stewardship – applying the right nutrient source at the right rate, at the right time and in the right place – is an innovative approach in fertiliser management. However, to meet the multi-dimensional goals of sustainable agriculture, appropriate performance metrics must be identified to assess the effectiveness of fertiliser management changes. One such metric is nutrient use efficiency (NUE). While 4R stewardship provides a framework that can result in improvements in NUE, implementation is greatly enhanced by the tools and technologies, associated with precision agriculture (PA). The purpose of this paper is to highlight current PA strategies that have the potential to increase NUE. Variable rate nitrogen (N) management using crop sensors is one technology that has resulted in improvements in NUE compared with standard, uniform N rates and other site-specific VRN management tools. Combining crop sensors with soil-based management zones (MZ) can further enhance the efficiency of fertiliser inputs. Other research has demonstrated that mounting crop sensors on an unmanned aerial vehicle (UAV) can provide a viable alternative to ground-based sensors while eliminating some of the obstacles to grower adoption of sensor technology. Implementing PA technologies within the context of 4R nutrient stewardship is an efficient and effective way to achieve the goals of sustainable agricultural systems.

Introduction

Goals of sustainable agriculture

In its simplest form, the goal of sustainable agriculture is the production of food, feed, fibre and fuel, without compromising the ability of the future generations to do the same. Thoughts on exactly how this goal should be accomplished are numerous, but one generally agreed upon fact is that concept of sustainable agriculture is multi-dimensional. The concept of sustainability does not apply to economic, environmental, or social drivers as independent of one another, but to all simultaneously. These three sustainability components represent various forms of capital including natural, social, human, physical, and financial (UNCTAD-UNEP, 2008) that will demonstrate resiliency and growth in a sustainable agricultural system. One of the biggest future challenges for sustainable agriculture will be meeting the global food demands that are expected to increase by 100 to 110% by 2050 (Tilman et al., 2011). A key contributor to this necessary increase will be the appropriate use of mineral fertiliser. It is difficult to determine exactly how much crop yield is due to the use of mineral fertiliser because of various factors including inherent soil fertility, climatic conditions, crop rotations, tillage, etc. However, Stewart et al. (2005) reviewed 362 seasons of crop production results and reported at least 30 to 50% of crop yield can be attributed to mineral fertiliser inputs. However, when used at the wrong time, in the wrong, place, in the wrong form, or at the wrong rate, mineral fertiliser can have negative impacts on sustainability. An essential tool in developing nutrient management strategies that will meet the food demands of a growing population, while considering the economic, environmental, and social dimensions of sustainable agriculture, is 4R nutrient stewardship.

4R nutrient stewardship and precision agriculture

4R nutrient stewardship is an innovative approach that provides a global framework for sustainable fertiliser management (IPNI, 2012). At the core of the framework is a simple concept – apply the "right" nutrient source at the "right" rate, at the "right" time, and in the "right" place. Hence, the four "rights' or 4Rs. The novelty of this approach is not in the 4Rs themselves, but in the recognition of the interconnectedness of all four components and the necessity to consider all four simultaneously when determining fertiliser best management practices. What is also unique about the approach is that what is determined to be the "right" combination of practices is site-specific, knowledge-intensive, and relevant to the context of the cropping system. The site-specificity of the 4Rs leads to the common question "How does precision agriculture

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‘fit in’ to the 4Rs?” The answer is that it’s not a matter of one concept fitting into another, but rather a realization that they are one in the same – 4R is precision agriculture. While the fundamental principle of 4R stewardship is applying the right source at the right rate, at the right time, and in the right place, precision agriculture is focused on “getting it right” by incorporating as much local information as possible in the management decision-making process and employing the appropriate tools, technologies and information management systems in the farming operation to get it done. The end result for both the 4Rs and precision agriculture is whole farm management of a sustainable agricultural system. The practices selected are also directly tied to sustainability goals for the operation, which are aligned with general goals for sustainable development for the region as identified by local stakeholders. Evaluation of the performance of practices with regard to the economic, environmental, and social priorities of the operation is done using indicators selected in agreement between the producer and the stakeholders. One performance indicator that is garnering increasing attention in current discussions on sustainable agriculture is nutrient use efficiency (NUE).

Nutrient use efficiency
Nutrient use efficiency is a key metric of sustainable crop nutrition as it reflects responsible management as well as relates to the risk of nutrient loss to the environment. However, NUE only addresses some aspects of the overall cropping system and must always be considered in the proper context. For example, management practices that increase NUE but result in lower productivity would not be considered sustainable. Conversely, a low NUE would not necessarily be indicative of an unsustainable practice as applied nutrients can remain in the soil without posing a threat to the environment. Sustainable nutrient management practices must be both efficient and effective. Despite the complexity of the term, NUE is an important concept for evaluating nutrient management practices and improving NUE has been listed among todays most critical and daunting research issues (Thompson, 2012).

The objective of this paper is to highlight precision agriculture technologies that when used within the context of 4R nutrient stewardship have the potential to result in improvements in NUE. Specifically (1) variable-rate N (VRN) application using crop sensors; (2) integrating crop sensing and soil properties for VRN management; and (3) using an unmanned aerial vehicle (UAV) as a crop sensor platform for VRN management.

Variable-rate N applications using crop sensors
Crop canopy sensing has been widely researched and is becoming an accepted practice for determining in-season crop N needs in several countries around the world. There are several commercially available crop sensors including GreenSeeker (Trimble Navigation, Sunnyvale, CA, USA), Crop Circle (Holland Scientific, Lincoln, NE, USA), and CropSpec (Topcon Precision Agriculture, Livermore, CA, USA). All of these sensors are active, meaning they have their own light source, which eliminates the problems associated with ambient light such as cloud cover, low light intensity, shadows, etc. The basic function of all forms of these sensors is to emit light in the visible and near-infrared spectrum and measure reflected light from the crop. Sudduth et al. (2015) evaluated the aforementioned sensors for their ability to discriminate reflectance differences related to maize N health and found that while the operational characteristics of the sensors varied, data from the nadir-looking sensors (GreenSeeker and Crop Circle) were highly correlated with each other and well correlated with maize biophysical data. The CropSpec is an oblique-looking sensor and reflectance measurements were less strongly related to those collected using the other sensors.

Most of the research to date has been focused on developing algorithms that will transform sensor output data, typically in the form of a normalized difference vegetation index (NDVI), into N-rate decisions for the growing crop. Nitrogen rate algorithm development work has been done in a variety of crops including wheat (Raun, et al., 2002), maize (Solari et al., 2008), cotton (Oliveira et al., 2013), rice (Harrell et al., 2011), and sugarcane (Lofton et al., 2012). Most all of the published algorithms have been sensor-specific and incorporate a variety of site-specific information depending on the sensor system being used. The reliance on these complex algorithms has resulted in slow commercial adoption rates despite well-documented success in both small- and large-scale research and demonstration studies.

Thomason et al. (2011) conducted some of the earliest farm-scale, sensor research. They established 15 replicated studies in commercial fields throughout the Coastal Plain region of Virginia, USA. Individual plots were 18.2 m wide and 100 to 122 m in length. Treatments were arranged in a randomized complete block design with six replications and included a standard treatment where the applied N rate was based on tissue N concentration, a variable-rate N treatment applied using a GreenSeeker RT 200 system, which was based on the Virginia wheat algorithm (VWA) they developed in their small plot research (Thomason et al., 2011), and a fixed-rate N treatment that was equal to the average of the VWA recommended rates. Nitrogen source was urea ammonium nitrate (30-0-0) and applications were made using a Spra-coupe 220 self-propelled sprayer (AGCO, Duluth, GA, USA) equipped with a 18.2-m boom, a Raven 440 flow rate controller (Raven Industries, Sioux Falls, SD, USA), and TeeJet 11008 or 11006 nozzles (TeeJet technologies, Glendale Heights, IL, USA). Their results showed that the standard GS30 N rate (determined based on tissue N content) and the rate determined using the VWA resulted in yields that were similar at 13 of the 15 sites (Figure 1). The VRA resulted in higher yield at one site and lower yield at another. However, recommended N rates were lower using the VWA at 9 sites by an average of 12 kg/ha, representing a decrease in average N recommendation of approximately 7% (Figure 1), which would result in a higher NUE. The fixed-rate treatment equal to the VWA average recommended rate resulted in lower yields compared to those found in the VWA or standard rates; thus, emphasizing the need to treat the spatial variability of N need in order to achieve comparable yields with N rate reductions (data not shown).

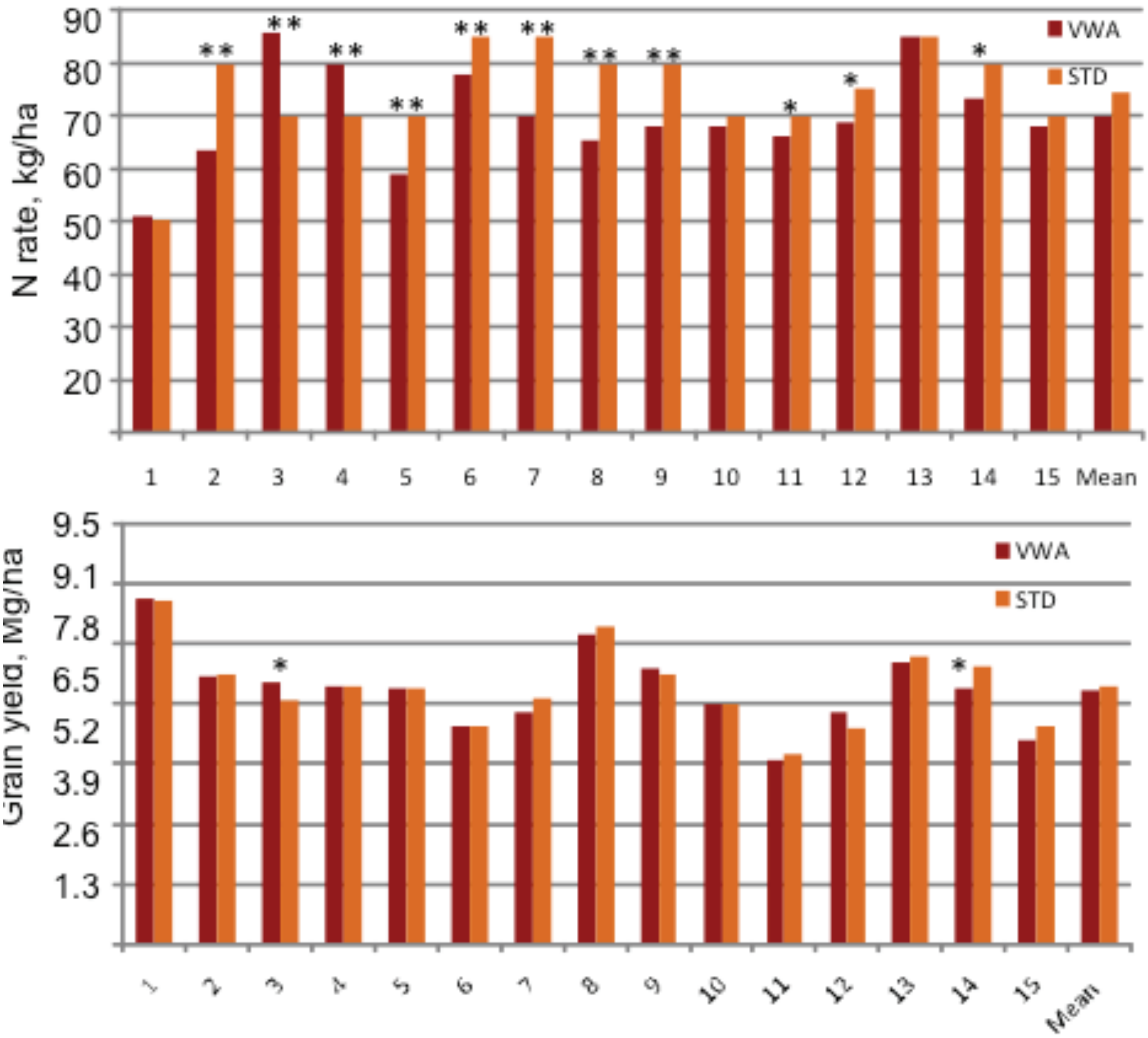


Figure 1. Mean grain yields and topdress N rates determined using the Virginia wheat algorithm (VWA) applied via GreenSeeker versus the standard (STD) method of using tissue N concentration at growth stage (GS) 30 for 15 sites in Virginia.

In more recent work, Chim et al. (2014) compared the GreenSeeker with other site-specific N rate decision support systems. In addition to GreenSeeker, they evaluated the Maize-N computer simulation program (Yang, 2015) and the Nutrient Expert software (IPNI, 2015) compared with the standard yield goal-based N recommendation for maize in VA. They found that all of the site-specific methods resulted in higher grain yield than the yield goal-based method, but NUE varied among methods (Figure 2).

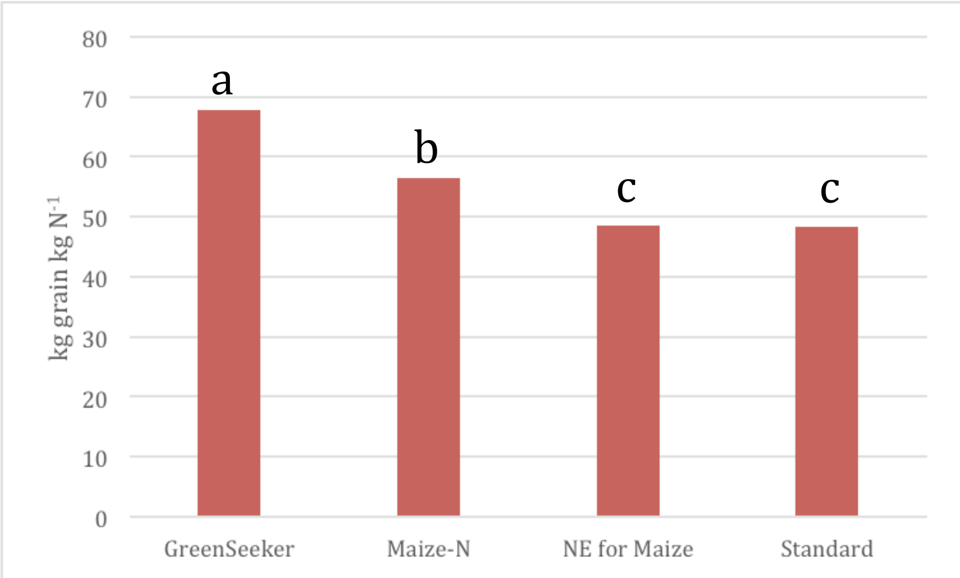
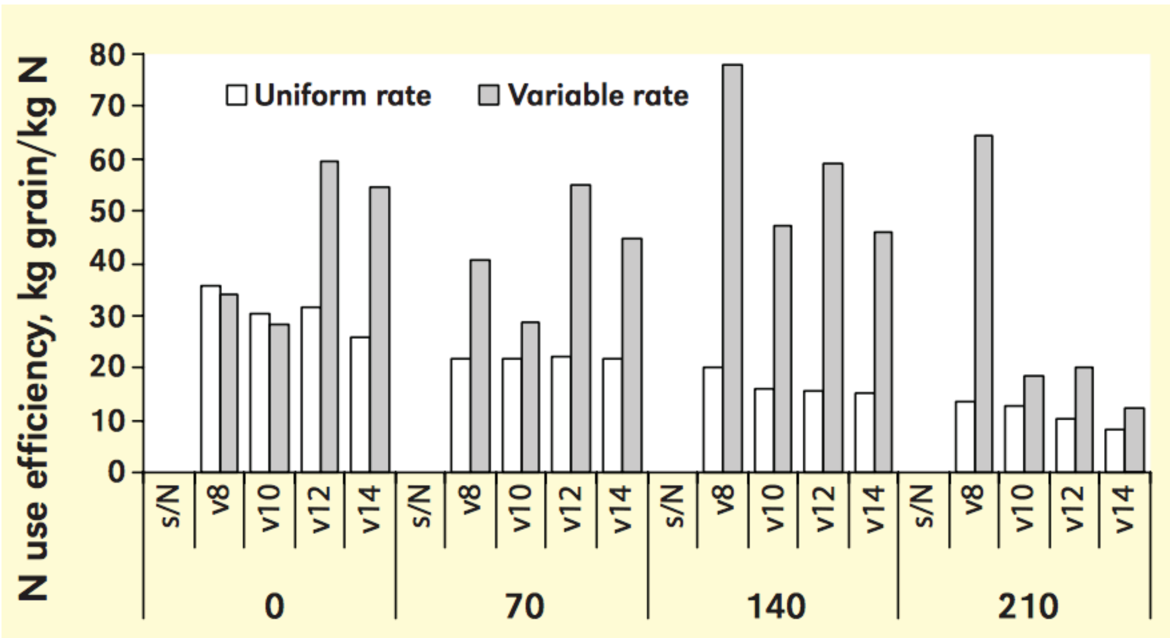


Figure 2. Nitrogen use efficiency, calculated as kg grain per kg N fertiliser applied via various decision support systems averaged over seven locations in Virginia, USA.

Melchiori (2010) also reported increased NUE in maize using GreenSeeker-based N rates compared with a standard fixed rate. Their work covered seven growing seasons in Argentina and evaluated the ability of the GreenSeeker to determine optimum sidedress N rates for maize across a range of growth stages and pre-plant N rates. Similar to other published studies, they found no difference in grain yield between the methods, but a higher NUE when using the sensor-based system (Figure 3).

Figure 3. Nitrogen use efficiency in maize following N fertilization between V8 and V14 using sensor-based variable rates or uniform fixed rates at varying levels of pre-plant N fertilization.



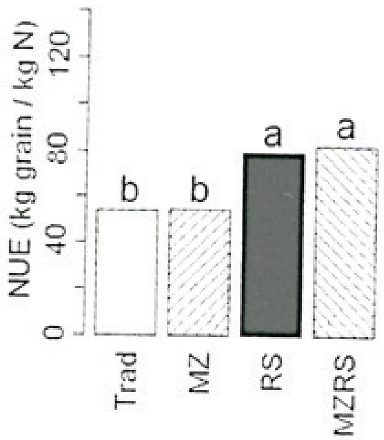
The commercial use of crop sensors has begun to increase more rapidly in the past few years, particularly in the U.S. and Europe. In late 2012, the US-based website, precisionag.com, released its annual ranking of the top trends in precision agriculture. Crop canopy sensors were identified as the "up and coming" technology to watch for. This was an interesting prediction because at the time, only 4% of precision ag service providers were offering sensor-based N fertilization (Holland et al., 2013). However by the end of 2013, crop sensing service offerings had nearly doubled among Midwestern US service providers (Erickson and Widmar, 2015); however this still only represented 7% of dealerships, while 70% of those same dealerships offer VR fertiliser application based on soil maps. Reasons for the slow adoption since sensors first became commercially available a decade ago have to do with various factors. One that was mentioned earlier is the complexity and "black box" aura of the N rate algorithms. Growers don't want to be overwhelmed with highly sophisticated decision support systems, but they do need some assurance that there is value in what they are paying for. Another has been an early lack of technical support from the manufacturers for some of the sensors. This obstacle is being addressed as less than 20% of dealers find a lack of manufacturer support to be a major obstacle for adoption (Erickson and Widmar, 2015). Another improvement that should lead to higher adoption rates is that as precision agriculture becomes more and more data-driven, multiple layers of information, such as various soil properties, can be incorporated into, or used to complement, the existing algorithms, creating a more robust prescription service for growers.

Integrating crop sensing and soil properties for VRN management

The benefit of dividing fields into homogeneous areas and treating the areas as independent management zones (MZ) is well documented (Khosla et al., 2002; Koch et al., 2004). Various layers of site-specific information such as soil fertility, soil organic matter, soil texture, grain yield, soil EC, and others are combined and similar areas with regard to productivity are delineated. Several of these layers are commonly offered both for collection and analyses by precision ag service providers (Erickson and Widmar, 2015). Nearly 70% of dealers in the Midwestern US offer GPS-based grid soil sampling; 60% conduct GPS-based field mapping, and over half offer yield monitor data analysis. Half of the dealers also offer satellite imagery, another popular layer for MZ delineation (Erickson and Widmar, 2015). Managing fields based on zones has been shown to improve grain yield, nutrient uptake and NUE (Khosla et al., 2002; Koch et al., 2004). Management zones are also effective as part of a 4R approach as they help guide the right fertiliser rate to the right place in the field and have been shown to result in increased profitability and reductions in excess nutrient loading that could have the potential to negatively impact the environment. Despite the clear benefit to MZ and the aforementioned value associated with crop sensing, few studies have investigated the potential to incorporate both approaches into a single management strategy.

Longchamps et al. (2015) conducted a three-year study in a 4.5-ha field in Colorado, USA to determine whether VRN management using both MZ and crop sensors would improve NUE over MZ or crop sensors used alone or the traditional single-rate approach. Management zones were delineated for the study according to the procedures described by Hornung et al. (2006). Data layers included: bare soil aerial image, the farmer's perception of the topography data, and farmer knowledge regarding soil management and productivity zones. Zones were then classified as low, medium, and high according to productivity. Sensor data were collected using a GreenSeeker sensor. Data processing and analyses, as well as, N rate assignments to zones and spatial distribution of treatments in the field are reported in Longchamps et al. (2015). Their results demonstrated that NUE was improved with both VRN strategies using the sensor over the traditional or MZ approaches (Figure 4).

Figure 4. Average NUE obtained using different management strategies; Trad - traditional uniform N rate; MZ – VRN based on management zones; RS – VRN based on crop sensing; MZRS – VRN based on combination of management zones and crop sensing.



Using UAVs as a crop sensor platform

While nearly all precision ag services are expected to increase in the next three years, the one poised to make the biggest leap is the use of UAVs (Erickson and Widmar, 2015). Thirty-eight percent of dealers expect to be offering UAV-related services by 2018, up from 19% in 2015. Commercial data collected using UAVs have included harvest and planting videos, crop scouting imagery and NDVI images. The NDVI maps have been used to develop variable rate N application maps so the question can be raised, "Can an active crop sensor be mounted on a UAV for VRN management?" The earliest answers are coming out of a research group at the University of Nebraska, USA. Krienke et al. (2015) conducted a study in the summer of 2014 to compare normalized difference red edge (NDRE) reflectance measured using a ground-based with a UAV-mounted crop sensor. The sensor used was a handheld Crop Circle Rapidscan and the UAV was a MikroKopter OktoKopter XL (MikroKopter, Moormerland, Germany). They compared the two platforms viewing actively growing turfgrass and maize crops. Specific details of the experimental methods are reported in Krienke et al. (2015). Their results showed a strong correlation between measurements collected using the handheld sensor (HA) and the UAV-mounted sensor (Figure 5).

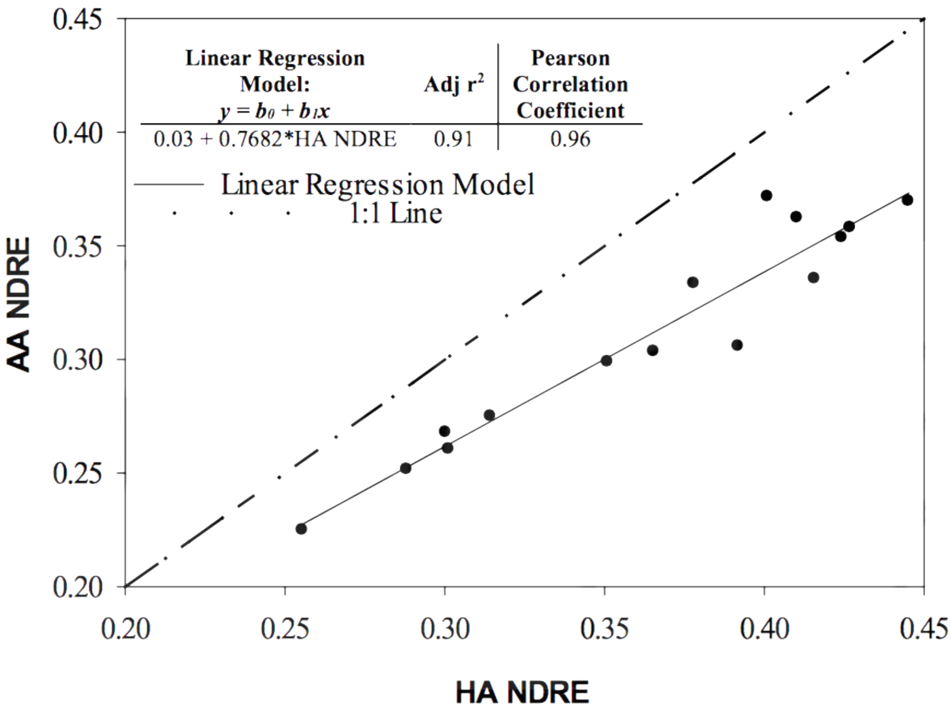


Figure 5. Regression relationship of NDRE reflectance between handheld (HA) and UAV (AA) sensor platforms.

These data suggest that the UAV platform is a viable replacement for ground-based sensors; however, their results also demonstrated a height effect on NDRE measurements. They recommended that UAV-based NDRE measurements be taken between 0.5 and 1.5 m above the crop canopy when being used for making variable rate N recommendations. The ability to mount crop sensors on UAVs should further contribute to the adoption of sensor technology as a VRN management strategy because one of the complaints of growers reluctant to adopt the technology is that the on-the-go nature of the current sensor systems makes them uncomfortable, as they can't preview the N rates prior to application in the field. UAV-mounted sensors will also add value to the system by allowing post-fertilization mapping to estimate crop responsiveness to N.

Conclusions

To meet the food production challenges for a growing population in a sustainable manner, continuous improvement in agricultural system performance will be required. This improvement will depend on a combination of technology, agronomy, management and policy support developments, and changes must occur across several disciplines of agriculture and society. Implementing PA technologies within the context of 4R nutrient stewardship is an efficient and effective way to help meet the environmental, economic and social goals of sustainable agricultural systems.

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