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Prediction of Maize Yields from In-Season GreenSeeker Normalized Difference Vegetation Index and Dry Biomass as Influenced by Different Nutrient Combinations

Hillary M. O. Otieno[1], George N. Chemining'wa[1] & Shamie Zingore[2]

[1] Department of Plant Science and Crop Protection, University of Nairobi, Nairobi, Kenya

[2] African Plant Nutrition Institute, Nairobi, Kenya

Correspondence: Hillary M. O. Otieno, Department of Plant Science and Crop Protection, University of Nairobi, Nairobi, Kenya. E-mail: hillarymoo@yahoo.com

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Abstract

To mitigate low maize productivity, improve on-farm planning and policy implementation, the right fertilizer combinations and yield forecasting should be prioritized. Therefore, this research aimed at assessing the effect of applying different nutrient combinations on maize growth and yield and in-season grain yield prediction from biomass and normalized difference vegetation index (NDVI) readings. The research was done in Embu and Kirinyaga counties, in Central Kenya. Nutrient combinations tested were P+K, N+K, N+P, N+P+K, and N+P+K+Ca+Mg+Zn+B+S. The results showed consistently lowest and highest NDVI reading, dry biomass, and grain yields due to P+K and N+P+K+Ca+Mg+Zn+B+S treatments, respectively. Positive NDVI responses of 56%, 14%, 15%, and 15% were recorded with N, P, K, and combined Ca+Mg+Zn+B+S, respectively. These nutrients, in the same order, recorded 54%, 20%, 8%, and 18% positive responses with biomass. The GreenSeeker NDVI reading with grain yield and aboveground dry biomass with grain yield recorded R^2 ranging from 0.23-0.53 and 0.30-0.61 (in Embu), and 0.31-0.64 and 0.30-0.50 (in Kirinyaga), respectively. When data were pooled, the prediction strength increased, reaching a maximum of 67% and 58% with NDVI and biomass, respectively. Yield prediction was even more robust when the independent variables were combined through multiple linear model at both 85 and 105 days after emergence. From this research, it is evident that the effects of balanced fertilizer application are detectable from NDVI readings—providing a tool for tracking and monitoring nutrient management effects—not just from the nitrogen perspective as commonly studied but from the combined effects of multiple nutrients. Also, grain yield could be accurately predicted early before harvesting by combining NDVI and biomass yields.

Keywords: biomass, fertilizer response, GreenSeeker, in-season yield prediction, maize, NDVI

1. Introduction

Maize (*Zea mays*) is a vital crop in the livelihoods of families in Sub-Saharan Africa (SSA). The crop is a source of food, livestock feed, fuel, and thatching materials, among other uses. As a food, maize is the most consumed crop in the region with annual per capita consumption ranging from 31 to 180 kg per person (Awika, 2011; Abate et al., 2015; Kornher, 2018). As a result, food security is always defined based on the availability of maize in these countries. Across Africa, the production has increased in terms of acreages but yields have remained relatively low, less than 2 t ha^{-1}, under conventional farmers' practices (Otieno et al., 2020). Breaking this cycle of low maize yield and food insecurity requires investments in breeding high yielding and stress-tolerant crop varieties, accurate weather forecasting, optimal soil and water management and other emerging technologies that optimize resource use. In responding to this need, researchers have come up with various interventions ranging from soil acidity management (Otieno et al., 2018; Fontoura et al., 2019), manure application (Naramabuye et al., 2008; Otieno et al., 2018), inorganic fertilizer application (Otieno, 2019; Otieno et al., 2020), to soil water management through reduced tillage and mulching (Murungu et al., 2011; Otieno et al., 2020). Most of these strategies and technologies have resulted in increased grain yield. Farmers and policymakers always wait until the dry harvesting stages to estimate the yields before proceed to draft and implement new plans and policies in the region. This method of assessing and measuring yields after harvesting usually comes late, leading to poor food insecurity mitigation planning and budgeting by governments and policy-makers. Thus, researchers are coming up with strategies to help in the early detection of possible constraints and likely expected yields based on in-season crop behaviors—yield forecasting. The importance of yield forecasting has been summarized by Habyarimana et al. (2019): provides data to governmental structures, companies, and farmers, which results in strategic advantages such as the rationalization of policy adjustments, price predictions and stabilization, efficient agricultural trade, and simplification of business operations particularly through planning harvest and delivery of the product, better deployments of machinery and logistics, and better management at the end-user level. The commonly used methods of weather, pest, disease and yield forecasting are crop modeling and remote sensing. These forecasting methods use parameters such as normalized difference vegetation index (NDVI), leaf area index, and fraction of absorbed photosynthetically active radiation (fAPAR) (Diouf et al., 2015; Kross et al., 2015; Ngoune et al., 2020). These technologies have evolved and converted into simpler farm tools and equipment for daily use by farmers. For instance, GreenSeeker NDVI equipment, a cheap hand-held remote sensing tool farmers are currently using to make in-season assessment of daily crop health (Verhulst & Govaerts, 2010; Sultana et al., 2014; Kitić et al., 2019; Ngoune & Mutengwa, 2020). However, farmers in Africa, and Kenya in particular, have not been able to use the GreenSeeker NDVI tool to assess the health of their crops and make rapid yield predictions early in the season for prompt farm budgeting and decision making. Thus the region is left out in the use of the technology. And this has exposed farmers and the entire population to chronic food insecurity that would otherwise be managed to some extent. Several researchers have used GreenSeeker NDVI equipment in fertilizer management and yield forecasting tool—reporting significant positive relationship between NDVI and crop N demand (Xia et al., 2016; Ali et al., 2018), biomass prediction (Xia et al., 2016) and grain yield prediction (Sultana et al., 2014; Fernandez-Ordoñez & Soria-Ruiz, 2017). This shows the usefulness of the tool in nutrient management and yield forecasting. In terms of plant health and nutrient management, however, most research has focused on nitrogen use efficiency only (Teboh et al., 2012; Quebrajo et al., 2015; Vergara-Díaz et al., 2016), leaving other nutrients unaccounted for in balanced nutrient requirements for improved crop production. Again, a few researches have looked at the effects of different nutrient combinations on crop's NDVI at different growth stages and how this translates to yield. This research therefore, aimed at investigating this effect. Again, researchers have shown relationships between crop NDVI and biomass and NDVI and grain yield through linear regression models. However, there are no evaluations done to show the effect of combining NDVI reading with its corresponding biomass on grain prediction in Sub-Saharan Africa. This gap could be explored for possible stronger yield predictions. Due to the above research gaps, this research therefore, aimed at assessing the effect of applying different nutrient combinations on maize growth and yield. It also evaluated the potential of in-season grain yield prediction from biomass and NDVI recording. The combination of different nutrients at plot level is important as it, to some extent, portrays the likely heterogeneity in maize growing conditions and interactions between nutrients between farms that have always complicated the expression in NDVI reading.

2. Material and Methods

2.1 Description of the Study Site

The trials were carried out in Kenya Agricultural and Livestock Research Organization (KALRO), Embu research station located in Embu County (Referred as Embu hereafter), and Kirinyaga Technical Institute (KTI) research fields located in Kirinyaga County (Referred as Kirinyaga hereafter). These sites cover agriculturally important zones where farmers predominantly grow maize as a source of food. The sites were located in the Upper Wet Mid Altitude Mega-environment. The sites are characterized by bi-modal rainfall patterns, experiencing wet seasons from March to June (long rain season) and September to December (short rain season). The annual rainfall ranges from 930 mm to 1550 mm. The daily mean temperature is about 18 ºC in Embu and 23 ºC in Kirinyaga. The soils in these sites are predominantly Humic Nitisols with clay-loam texture, deep and good water-holding capacity (Jaetzold & Schmidt, 1983). Other site-specific soil fertility characteristics of the study sites were as reported by Otieno et al. (2020). The research was done during the 2013/2014 short rains and 2014 long rains seasons.

2.2 Experimental Design and Treatments

The experiment was laid out in a randomized complete block design with each treatment replicated six times. Each plot measured 8 m × 10 m with a space of 1.5 m and 1 m left between blocks and plots, respectively. Between blocks, a trench of 1 m wide and 1 m deep was dug to reduce the chances of nutrients flowing within the soil profile from one plot to the other. The treatments comprised of different nutrient combinations: P+K, N+K, N+P, N+P+K, and N+P+K+Ca+Mg+Zn+B+S. Nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), zinc (Zn), boron (B), and sulfur (S) nutrients were applied at the rates of 120, 40, 40, 10, 10, 5, 5 and 26.3 kg ha^{-1}, respectively. The nutrients were supplied from urea, triple superphosphate, muriate of potash, calcium sulfate, magnesium sulfate, zinc sulfate, borax, and sulfate sources, respectively. These rates were chosen to ensure maize growth was no limited by nutrients and to target at least 6 tons of grains per hectare. Nitrogen was applied in three equal splits (at planting, V4, and V10 stages of maize vegetative growth) while the rest of the nutrients were applied at planting. Maize variety, DK 8031, was selected and used for the trials in all sites. This maize variety was selected due to its extensive use in the region and adaptability to the prevailing climatic conditions.

2.3 Agronomic Practices

The research was done during the 2013/2014 short rains and 2014 long rains seasons. During the 2013/2014 short rain season, DK 8031 maize variety was planted to deplete nutrients from the plots to reduce huge variability due to already present nutrients. Tilling of plots was done a week to the 2014 long rain season using hand-hoes. After three consecutive rains, maize planting was done at 75 cm by 25 cm spacing using a calibrated planting string. At planting, fertilizers were placed in planting holes then mixed with soil before placing seeds to avoid direct contact with fertilizer. Two maize seeds were planted per socket and thinned to one plant per socket seven days after emergence to maintain a population of about 53,000 plants per hectare. The first and second weeding and topdressing (on plots that received N) were done at V4 and V10 stages of maize growth. Pests and diseases were monitored regularly. At 30 days after emergence, Bulldock (Beta-Cyfluthrin 0.5 g/kg) pesticide was applied at the rate of 6 kg ha^{-1} to control stalk borers. During pesticide application, all protection measures as outlined by Otieno (2019) were observed. After maturity stage, dried cobs were harvested manually.

2.4 Data Collection

Maize Normalized Difference Vegetation Index (NDVI): Maize NDVI measurements were taken with GreenSeeker™ Handheld Optical Active Sensor (Trimble Navigation Limited, Sunnyvale, California, USA). The sensor emits brief bursts of red and infrared light and then measures the amount of each type of light that is reflected back from the plant; the measuring process continues as long as the trigger remains engaged (https://agriculture.trimble.com). The NDVI reading (ranging from 0.00 to 0.99) is displayed on the LCD screen of the equipment. The strength of the detected light is used to indicate the crop health; the higher the reading, the healthier the plants could be assumed to be. The NDVI measurements were taken at 40, 65, 85, and 105 days after emergence (DAE) in the central rows of all plots. Three readings were taken within each plot, leaving two maize rows from both edges. These readings were then averaged to give a plot reading.

Biomass production: Aboveground biomass production was assessed at 40, 65, 85, and 105 DAE. Biomass production from each treatment was computed from a sub-plot measuring 4.69 m^2 and a subsample containing chopped leaves and stalks weighing 500 g dried at 65 ºC to a constant dry weight. These weights were then used to compute dry biomass production per hectare using Dobermann and Walters (2005) formula.

Grain yield: Yields were computed from a net plot measuring 3.75 m by 4 m (15 m^2) taken from the center of each treatment plot leaving at least 2 m on each side of the net plot to minimize the edge effects. After harvesting, total plants and cob numbers were recorded, and total cob weight was determined in the field using a digital scale accurate to 2 decimal places. All cobs were shelled, mixed thoroughly, and a sub-sample of 1 kg grain (fresh weight) taken for further drying to a constant weight at 12% moisture content (dry weight). These weights were then used to compute grain yield production per hectare.

2.5 Statistical Analysis

Collected data were subjected to analysis of variance (ANOVA) using Genstat statistics software, 15th version. Where F tests were significant, means were compared using Fisher's protected least significance difference (L.S.D.) procedure at $p \leq 0.05$. The NDVI and biomass averages were then used to assess nutrient responses for individual nutrients and their combinations. Several simple and multiple linear regression models were investigated and compared for each site and pooled data. These regression models were done to establish the relationship between NDVI, biomass, and grain yield. Graphical presentations were done using excel package.

3. Results and Discussion

3.1 Effect of the Site and Nutrient Combinations on GreenSeeker Normalized Difference Vegetation Index (NDVI)

In Kirinyaga, the NDVI readings were 0.05 and 0.02, significantly higher than those recorded in Embu at 40 and 65 DAE respectively. However, this changed at 85 and 105 DAE, where Embu recorded 0.01 and 0.15 higher readings. The change in NDVI recordings was because during the first eight weeks after planting, Kirinyaga site received higher rainfall than Embu site, after which the latter site received more rainfall than the former site

(Otieno et al., 2020). These changes in rainfall received may have affected the general crop physiology as reflected on the NDVI measurements. Most studies on the effect of water stress on maize growth and production have demonstrated that increasing water stress above the tolerable levels significantly reduces growth and yield parameters (Khan et al., 2001; Li-Ping et al., 2006; Rimski-Korsakov et al., 2009; Zhou et al., 2020). Across the growth intervals, the NDVI readings were observed to increase from 40 DAE before peaking at around 85 DAE then decline towards 105 DAE (Figures 1 and 2). This finding is in line with observations in other studies. For example, Govaerts et al. (2006), when assessing the effect of conventional tillage and permanent raised beds with different crop residue management on soil C and N dynamics, reported an increase in NDVI reading that peaked at 60 days after emergence and a decline towards 100 days after emergence. During research on in-season prediction of corn grain yield potential using NDVI, Teal et al. (2006) observed an increasing NDVI value from maize growth stage V6 (NDVI = 0.22) through V7 and to peak at V8 (NDVI = 0.77) before declining towards V10/11 (NDVI = 0.40). Verhulst et al. (2010) also reported a steady increase in maize NDVI readings from planting up to about 58 days, after which the curve plateaued till around 80 days before beginning to decline towards 130 days. The rise in NDVI reading from planting could be due to increases in crop physiological activities (such as available water, nutrient, and sunlight absorption) required for active vegetative growth. The peaks coincided with the early reproductive stage when the crops acquire maximum chlorophyll concentration for cobing and grain filling processes that demand high photosynthates. The decline in NDVI observed after achieving the peak could be due to degeneration of cells that reduce their capacity to absorb PAR (Gamon et al., 1997; Raun et al., 2001).

	40 DAE	65 DAE	85 DAE	105 DAE
L.S.D.	0.023	0.015	0.012	0.019
P-value	<0.001	0.036	0.030	<0.001

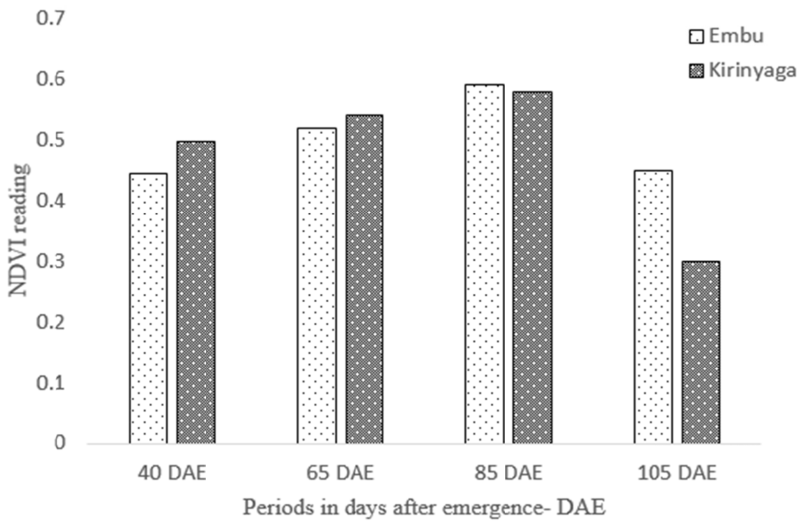


Figure 1. Effect of the site on maize GreenSeeker Normalized Difference Vegetation Index (NDVI) reading at 40, 65, 85, and 105 days after emergence (DAE)

The application of different fertilizer combinations also significantly influenced the NDVI readings across the entire growth intervals considered ($p < 0.001$) (Figure 2). Nutrient combinations showed similar curve trends in NDVI reading (Figure 2). Application of P+K and N+P+K+Zn+B+Mg+Ca+S nutrient combinations recorded significantly lower and higher NDVI readings, respectively, than other nutrient combinations (Figure 2). The N+P and N+K combinations recorded statistically similar NDVI values across the entire growth periods. Application of phosphorus and potassium alone (P+K treatment) is not enough for better maize production. From the NDVI reading, it is evident that maize requires different nutrient combinations- as many nutrients were combined, the NDVI values were observed to increase. Such response is expected due to the high levels of nutrient depletion that have occurred in the region over the decades (Henao & Baanante, 1999). When macronutrients are applied together, they work in synergy to boost plant growth and yield (Rietra et al., 2017). For instance, there are known positive synergistic interactions between P x N and K x N (Aulakh & Malhi, 2005).

However, micronutrients should be used cautiously within the optimal rates to avoid common antagonism leading to deficiencies or toxicity (Rietra et al., 2017).

	40 DAE	65 DAE	85 DAE	105 DAE
L.S.D.	0.036	0.024	0.019	0.030
P-value	<0.001	<0.001	<0.001	<0.001

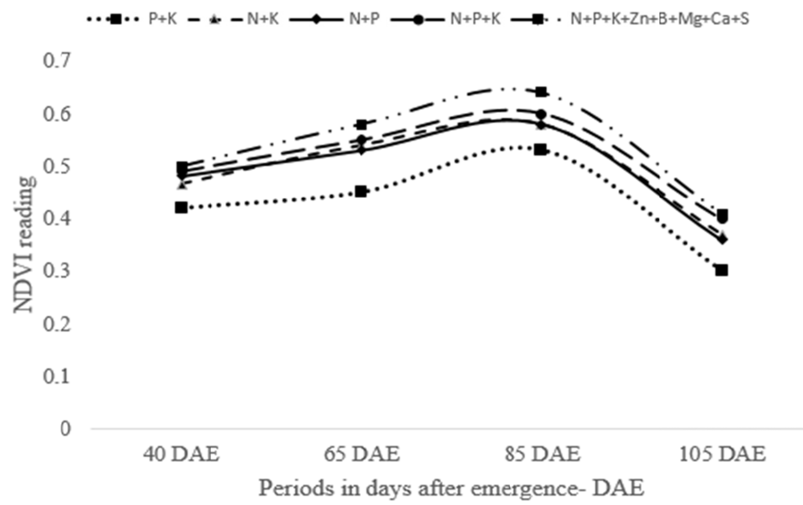


Figure 2. Effect of combining different nutrients on the maize GreenSeeker Normalized Difference Vegetation Index (NDVI) readings at 40, 65, 85, and 105 days after emergence (DAE)

The NDVI response to N, P, K, and combined secondary and micro-nutrients (Ca+Mg+Zn+B+S) application ranged from 0.07-0.1, 0.01-0.03, 0.0097-0.04, and 0.0095-0.0895, respectively (Figure 3). The applied N contributed 56% of the accumulative responses cross the growth intervals (Figure 3). This was followed by K and micronutrients, both at 15% and least by P at 14% (Figure 3). These findings show the importance of nitrogen in crop and the most limiting nutrient than the other nutrients. Alfoldi et al. (1994) and Bąk et al. (2016) also found a high concentration of N followed by K and least by P nutrients in maize leaves. Nitrogen is heavily involved in crucial plant metabolic and physiological processes including chlorophyll formation (Kirkby et al. 2009). Potassium is another indispensable nutrient in crop growth and development. Potassium plays a crucial role in photosynthesis, translocation of photosynthates, and metabolisms (Zorb et al., 2014; Du et al., 2019). This research has proved that K levels are getting below the critical levels in Kenya. The active involvement of phosphorus nutrient in maize growth and reproduction especially on chlorophyll and photosynthesis process is well documented by Carstensen et al. (2019). Hence, whenever deficient in the soils, maize will always respond to any extra application from external sources. Lastly, is the secondary and micronutrients; these are elements present in crops at concentrations of milligrams per kilogram dry matter (Kabata-Pendias, 2001). These elements equally play essential roles in maize growth. For instance, the application of calcium, magnesium, and zinc results in increased photosynthesis due to their influence on chloroplast pigments (Kösesakal & Ünal, 2009; Trankner et al., 2018). However, correct use of this class of crop nutrients is critical in ensuring better growth and high nutrient use efficiencies. For instance, Samreen et al. (2017) reported that the application of zinc from 1 μM to 2 μM reduces phosphorus uptake.

The highest but similar responses due to N application were recorded at 65 and 105 DAE. This trend was different from that showed by other nutrients—P, K and combined secondary and micro-nutrients recorded highest NDVI responses at 105, 105, and 85 DAE, respectively. The lowest responses were recorded at 40 and 85 DAE for N, 65 DAE for P, 40 DAE for K, and 40 and 105 DAE for micronutrient applications (Figure 3). The general low responses at 40 DAE for all nutrients could be due to the general low plant growth rate at these stages. Again, it could be due to small and fewer maize leaves hence low cover leading to low reflectance as not all the emitted rays from the GreenSeeker device hit the right targets. The interaction between site and nutrient combinations did not significantly affect NDVI reading (Table 1).

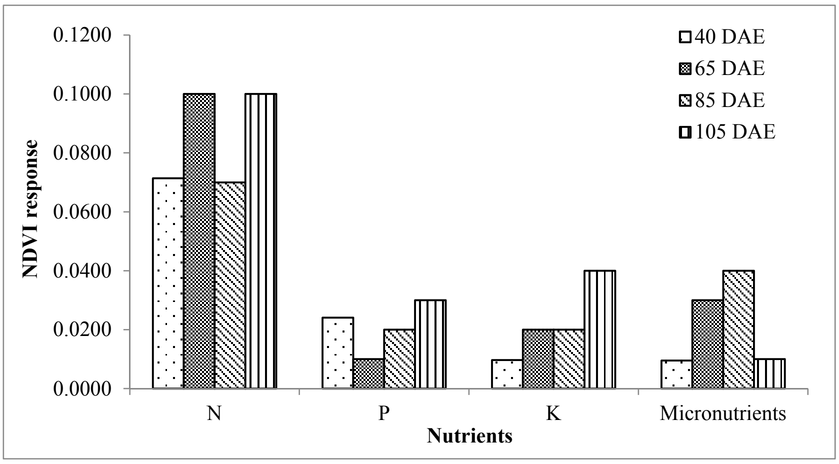


Figure 3. Maize GreenSeeker normalized difference vegetation index (NDVI) response to N, P, K, and combined secondary and micro-nutrients (Mg+Ca+S+Zn+B) application. The responses were calculated from the pooled data across Embu and Kirinyaga sites

Table 1. The interactive effect between site and nutrient combination on maize GreenSeeker normalize difference vegetation index (NDVI) readings at 40, 65, 85, and 105 days after emergence (DAE) in Embu and Kirinyaga sites

Nutrient combination	40 DAE		65 DAE		85 DAE		105 DAE	
	Embu	Kirinyaga	Embu	Kirinyaga	Embu	Kirinyaga	Embu	Kirinyaga
P+K	0.38	0.46	0.45	0.48	0.56	0.53	0.40	0.24
N+K	0.44	0.50	0.54	0.55	0.58	0.58	0.45	0.29
N+P	0.45	0.51	0.52	0.54	0.58	0.57	0.43	0.29
N+P+K	0.47	0.52	0.55	0.55	0.60	0.60	0.47	0.32
N+P+K+Zn+B+Mg+Ca+S	0.49	0.52	0.57	0.59	0.67	0.62	0.49	0.34
L.S.D.$_{(S \times NC)}$		0.051		0.034		0.027		0.043
P-value$_{(S \times NC)}$		0.819		0.474		0.472		0.946
CV%		9.2		5.5		3.9		9.9

3.2 Effect of Site and Nutrient Combinations on Aboveground Dry Biomass Production

The site significantly influenced dry biomass production ($p < 0.001$) (Figure 4) and by fertilizer application ($p < 0.001$) at 65, 85 and 105 DAE only (Table 2). Biomass production at 40 and 65 DAE was 0.19 and 1.8 t ha^{-1}, respectively, higher in Kirinyaga than in Embu while at 85 and 105 DAE, the trend changed and biomass was 1.15 and 1.42 t ha^{-1}, respectively, higher in Embu than in Kirinyaga (Figure 4). This trend is similar to that observed with NDVI readings and is attributed mainly to rain variations between sites.

The biomass increased from 40 DAE and peaked at 85 DAE before decreasing towards 105 DAE. This trend was observed both in Embu and Kirinyaga. This finding agrees with that reported by Otieno (2019) while evaluating the growth and yield response of maize to a wide range of nutrients on ferralsols of western Kenya. Similarly, in Central Brazil, Baldé et al. (2011) reported an increase in maize leaf area which peaked between 80-100 days before declining in size towards 180 days after planting. As cells increase in size and multiply in number, maize plants grow and thus increase in size. Consequently, the leaf area increases in size and number, and more photosynthates are accumulated resulting in high biomass production until the maximum size is attained (Bair, 1942; Kohl et al., 2017).

At 40 DAE, the effect of applying different nutrient combinations yielded non-significant differences in aboveground dry biomass. This could be due to low nutrients demanded by young maize seedlings. Hence the amounts that were supplied by the soil were optimal in keeping the same growth rate. As plants grow, the demand for nutrients increases leading to a slow growth rate for plants that cannot access adequate nutrients. At 65 DAE, P+K treatment recorded significantly lower dry biomass than all other treatments except N+K combination. Both N+P+K and N+P+K+Zn+B+Mg+Ca+S treatments recorded similar biomass. Throughout the growth stages, P+K and N+P+K+Zn+B+Mg+Ca+S treatments, respectively, recorded significantly lower and higher dry biomass than other treatments. Numerically, N+P+K treatments consistently recorded the second-highest dry biomass yield throughout the growth stages considered. Generally, application of a wide range of nutrients from external sources tends to increase maize performance whenever they are limited in supply from the soils (Kugbe et al., 2019; Otieno et al., 2020).

The consistent low biomass production under P+K nutrient supply showed that N was limiting in these regions—N response was at 54% (biomass yield response range = 0.16-2.61 t ha^{-1}) of the total biomass production (Figure 5). Several researchers have reported nitrogen to be the most limiting nutrient in the region, including Kenya (Kihara et al., 2016; Pasley et al., 2019). This was followed by K at 20% (biomass yield response range = 0.03-1.2 t ha^{-1}) and least by P at 8% (biomass yield response range = 0.06-0.53 t ha^{-1}) (Figure 5). This order contradicts reports by Kanyanjua et al. (2006) that showed low to no K application responses. Otieno et al. (2018) also reported maize response in decreasing order of N followed by phosphorus then potassium and least micronutrients. The importance of secondary and micro-nutrients is also becoming visible in the region. From this research, the combined response due to Zn+B+Mg+Ca+S application was higher than that of P nutrient- at 18% (biomass yield response ranging from 0.03 to 1.2 t ha^{-1}). In Ghana, Kugbe et al. (2019) confirmed this and reported a significant effect of including secondary and micronutrients (S, Zn and B) in the fertilization of maize. This order of response is similar to that reported with NDVI reading (Figure 3), hence illustrating the positive relationships that exist between these parameters in maize production. Despite the positive response, trace elements could also be detrimental to crops if applied above the recommended rates. According to Gupta and Gupta (1998) toxicity levels of trace elements range from 20 to 50 µg g^{-1} for copper and boron to several hundred µg g^{-1} for manganese, molybdenum and zinc. These nutrients also tend to have antagonistic effects resulting in low crop yields when applied with macronutrients (Rietra et al., 2017).

	40 DAE	65 DAE	85 DAE	105 DAE
L.S.D.	0.044	0.323	0.429	0.417
P-value	<0.001	<0.001	<0.001	<0.001

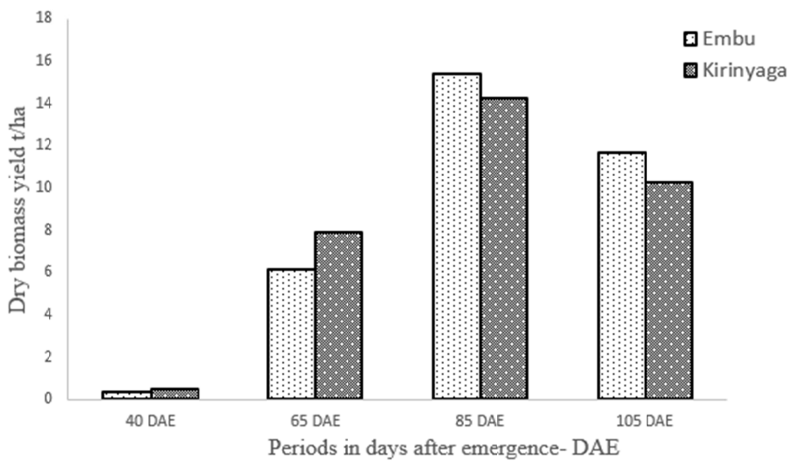


Figure 4. Effect of the site on maize aboveground biomass production at 40, 65, 85, and 105 days after emergence (DAE) at Embu and Kirinyaga

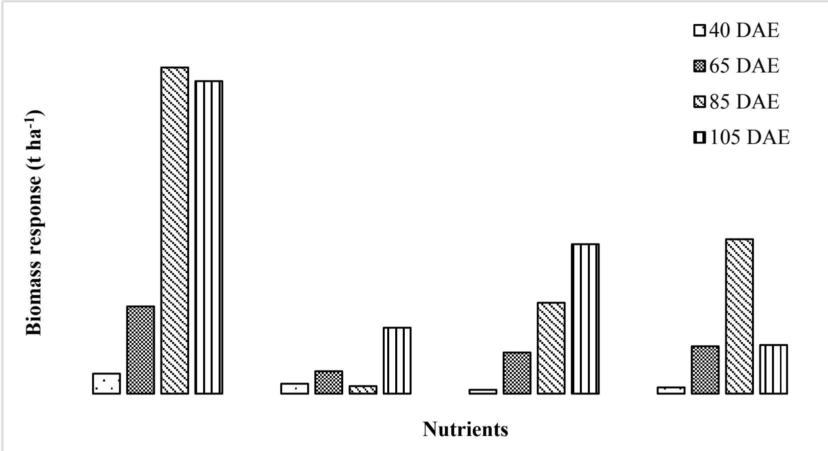


Figure 5. Maize biomass yield response to N, P, K, and combined secondary and micronutrients (Mg+Ca+S+Zn+B) application. The responses were calculated after pooling the data across Embu and Kirinyaga sites

The interaction between the site (S) and nutrient combination (NC) did not result in a significant difference in biomass production (Table 2). The numerically lowest biomass yields were recorded at 40 DAE, while the highest at 85 DAE. The biomass production varied between 0.25 and 0.64, 5.15 and 8.51, 12.35 and 17.45, and 8.19 and 13.11 t ha^{-1} at 40, 65, 85 and 105 DAE respectively.

Table 2. Interactive effect between site and nutrient combination on maize dry biomass yield (t ha^{-1}) at 40, 65, 85, and 105 days after emergence (DAE) in Embu and Kirinyaga trial sites

Nutrient combination	40 DAE		65 DAE		85 DAE		105 DAE	
	Embu	Kirinyaga	Embu	Kirinyaga	Embu	Kirinyaga	Embu	Kirinyaga
P+K	0.25	0.38	5.64	7.37	12.94	12.35	10.27	8.19
N+K	0.28	0.52	6.15	7.90	15.38	15.03	11.38	11.03
N+P	0.36	0.53	5.85	7.91	15.38	13.71	11.38	9.71
N+P+K	0.39	0.57	6.40	8.03	15.89	14.64	12.27	11.21
N+P+K+Zn+B+Mg+Ca+S	0.43	0.64	6.67	8.51	17.45	15.58	13.11	11.15
L.S.D.$_{\cdot(S \times NC)}$		0.09		0.72		0.95		0.93
p-value$_{(S \times NC)}$		0.660		0.934		0.049		0.050
CV%		19.3		8.8		5.6		7.3

3.3 Effect of the Site and Nutrient Combination on Maize Grain Yield

Site and nutrient combinations significantly affected grain yields (Table 3). The N+P+K+Zn+B+Mg+Ca+S treatment generally had significantly higher grain yield than N+K, N+P, and P+K across all sites and NPK treatment in Embu. The P+K treatment had a lower grain yield than N+P treatment at Kirinyaga. Nutrient combinations N+K, N+P, P+K, and N+P+K, were not significantly different in grain yield at Embu. At Kirinyaga site, no significant differences were recorded among N+P+K+Zn+B+Mg+Ca+S, N+P+K, N+K, and N+P treatments. There was no significant interaction effect observed between site and nutrient combinations. The positive effect of combining primary, secondary, and trace nutrients on grain yields has been confirmed in Ghana by Kugbe et al. (2019) and in Kenya by Muthaura et al. (2017), Njoroge et al. (2018), and Otieno (2019). Secondary and micro-nutrients are increasingly becoming important in Kenyan soils. Kihara et al. (2016) reported strong response to the application of secondary and micronutrients in the high and intermediate response classes in Kenya and other countries in Sub-Saharan Africa. Otieno (2019) also reported strong responses due to the application of Ca, Mg, Zn, B, and S in western Kenya.

Table 3. Effect of site and nutrient combination on maize grain yield (t ha^{-1}) at Embu and Kirinyaga

Nutrient Combination	Embu	Kirinyaga	Mean
P+K	5.00	4.20	4.60
N+K	5.10	4.50	4.80
N+P	5.10	4.70	4.90
N+P+K	5.20	4.70	4.95
N+P+K+Zn+B+Mg+Ca+S	5.70	4.80	5.25
Mean	5.22	4.58	
$L.S.D._{(Site-S)}$	0.49		
$L.S.D._{NC}$	0.35		
$L.S._{(S \times NC)}$	0.95		
$p\text{-value}_S$	<0.001		
$p\text{-value}_{NC}$	0.013		
$p\text{-value}_{(S \times NC)}$	0.076		

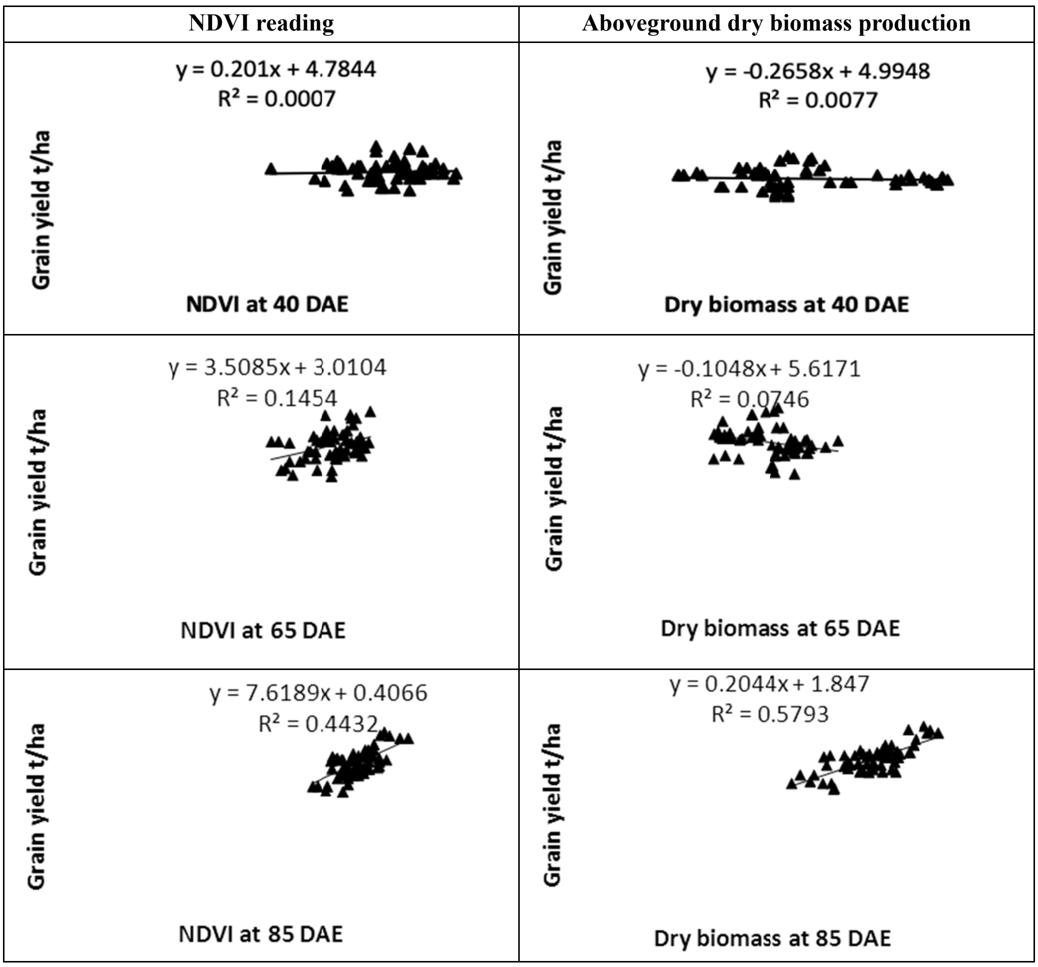
3.4 Predicting Maize Grain Yield from GreenSeeker Normalized Difference Vegetation Index (NDVI) Reading and Aboveground Dry Biomass

The in-season precision of predicting grain yield varied between sites and independent variables considered (Table 4). In all sites, there were significant positive relationships between grain and GreenSeeker NDVI reading and between grain and biomass. The GreenSeeker NDVI readings and aboveground dry biomass produced R^2 ranging from 0.23-0.53 and 0.30-0.61 (in Embu), and 0.31-0.64 and 0.30-0.50 (in Kirinyaga) respectively. The use of NDVI reading in predicting grain yields has been reported by several researchers (Sultana et al., 2014; Fernandez-Ordoñez & Soria-Ruiz, 2017; Maresma et al., 2020). The pooled GreenSeeker NDVI readings and aboveground biomass data recorded significant positive prediction of grain yield (Figure 6). The GreenSeeker NDVI were significant at 65 ($p < 0.0001$), 85 DAE ($P = 0.0185$) and 105 DAE ($P < 0.0001$) while aboveground dry biomass was significant at 65, 85 and 105 DAE ($P < 0.0001$). Both GreenSeeker NDVI reading and biomass showed an increasing strength in predicting maize grain as the measurements were taken towards crop maturation; R^2 ranged between 0.0007 (at 40 DAE) and 0.6683 (at 105 DAE) in the case of NDVI and between 0.0077 (40 DAE) and 0.57 (at 105 DAE) in the case of dry biomass (Figure 6). These R levels are well within the ranges reported by other researchers, 0.32-0.78 (Sultana et al., 2014; Naser et al., 2020). Whether at the individual sites or pooled data, stronger yield predictions were recorded from those variables collected towards the reproductive stages from 85 days and the best at 105 days after emergence. These findings resonate with those reported by Maresma et al. (2020) who concluded that best yield predictions are obtained by scanning maize at or after V10 stage of growth. Fernandez-Ordoñez & Soria-Ruiz (2017) also found strong yield prediction when NDVI was recorded at flowering. During the assessment of the usefulness of spectral reflectance indices as durum wheat yield predictors under contrasting Mediterranean conditions, Royo et al. (2003) concluded that the milky-grain stage is the best depictive stage for recording NDVI as it is more directly related to yield than earlier measurements.

When NDVI was combined with biomass collected at corresponding growth stages, the strength of grain prediction increased tremendously (Table 5) compared to when the relationship was considered at the individual site levels (Table 4 and Figure 6). In-season prediction of grain yield was very strong from 85 DAE (adjusted R = 0.706) to 105 DAE (adjusted R = 0.841). This could be due to the synergy resulting from the individual variables all linking towards grain prediction. Although there is no previous work showing this kind of prediction, Royo at al. (2003) found that combining NDVI with other parameters like reflectance at 550 nm (R550), water index (WI), photochemical reflectance index (PRI), structural independent pigment index (SIPI), and simple ratio (SR) explained a 95.7% of yield variability jointly when all the experiments were analyzed together compared to 17-65.2% when regressions were analyzed separately.

Table 4. Simple linear regression output showing the relationship between grain yield and in-season GreenSeeker normalize difference vegetation index (NDVI) reading and aboveground biomass production at four (4) different growth time intervals in Kirinyaga and Embu trial sites

Site	Dependent variable	Independent variable	Intercept	Slope	R^2	Slope significance
Normalized Difference Vegetation Index (NDVI)						
Embu	Grain yield	40 DAE	3.70	3.27	0.23	0.0071
	Grain yield	65 DAE	2.51	5.04	0.42	<0.0001
	Grain yield	85 DAE	1.07	6.89	0.53	<0.0001
	Grain yield	105 DAE	3.36	4.01	0.32	0.0010
Kirinyaga	Grain yield	40 DAE	2.71	3.77	0.31	0.0011
	Grain yield	65 DAE	2.25	4.32	0.48	<0.0001
	Grain yield	85 DAE	1.07	6.08	0.57	<0.0001
	Grain yield	105 DAE	3.00	5.41	0.64	<0.0001
Aboveground biomass production						
Embu	Grain yield	40 DAE	4.30	2.51	0.31	0.0014
	Grain yield	65 DAE	3.52	0.27	0.30	0.0017
	Grain yield	85 DAE	2.55	0.17	0.61	<0.0001
	Grain yield	105 DAE	2.89	0.19	0.45	<0.0001
Kirinyaga	Grain yield	40 DAE	3.77	1.55	0.49	<0.0001
	Grain yield	65 DAE	2.50	0.26	0.30	0.0017
	Grain yield	85 DAE	2.43	0.15	0.49	<0.0001
	Grain yield	105 DAE	3.10	0.15	0.50	<0.0001



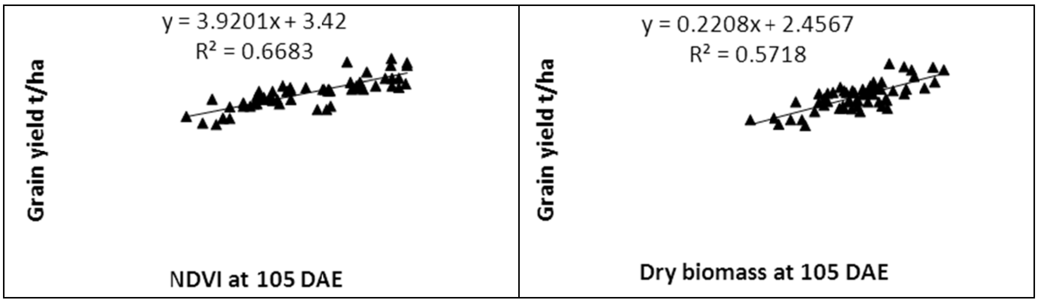


Figure 6. Relationship between grain yield and in-season GreenSeeker normalize difference vegetation index (NDVI) reading and aboveground dry biomass production at 40, 65, 85, and 105 days after emergence (DAE). The data here were pooled across Embu and Kirinyaga trial sites

Table 5. Multiple linear regression output showing the relationship between grain yield (dependent variable) and in-season GreenSeeker normalize difference vegetation index (NDVI) reading and aboveground dry biomass production (independent variables) recorded at 40, 65, 85, and 105 days after emergence (DAE) from the data pooled across Embu and Kirinyaga trial sites

Growth period	Observations	Standard error	Coefficients			Adjusted R	*P*-value
			Intercept	NDVI reading	Biomass yield		
40 DAE	60	0.437	4.414	1.684	-0.756	0.027	0.4544
65 DAE	60	0.356	3.404	5.291	-0.191	0.333	<0.0001
85 DAE	60	0.274	0.757	3.123	0.154	0.706	<0.0001
105 DAE	60	0.222	2.650	2.705	0.111	0.841	<0.0001

4. Conclusion and Recommendation

Maize growth and yield are strongly influenced by fertilizer application, with nitrogen and potassium being the most limiting, according to this research. The effects of balanced fertilizer application are detectable from NDVI readings—providing a tool for tracking and monitoring nutrient management effects—not just from the nitrogen angle but from the combined effects of multiple nutrients. The use of secondary and micro-nutrients was observed to show responses in Embu and Kirinyaga regions. However, the individual effects could not be separated due to the setup of this research. This is one of the gaps that should be investigated further. Better management of fertilizers and yield forecasting could be done remotely by using the GreenSeeker Normalized Difference Vegetation Index (NDVI) handheld device. This research has proved that a strong prediction could be made as early as 85 days after planting maize—44-58% of the expected yield. The prediction is even much more substantial when done 20 days later, —57-67% of the expected yields could be predicted. Multiple linear regression analysis model combining NDVI and dry biomass collected at corresponding periods could be claimed to offer the best model of in-season maize grain yield prediction. Between 85 and 105 days after emergence, this model predicted grain yield with much precision 71-84%. Therefore, combining NDVI and dry biomass collected between 85 and 105 days after maize emergence provides the best model for predicting maize yields. These periods are early enough to allow better planning by key players- government, policymakers, agro-input manufacturers, logistic companies, and farmers.

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