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Unraveling the Relationship between Soil Nutrients and Maize Leaf Disease Occurrences in Mopani District Municipality, Limpopo Province, South Africa

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Abstract: Maize is a staple crop important for food security that millions globally depend upon as an energy source, primarily due to its high starch and fat content. For growth and disease resistance, maize production requires a balanced intake of essential nutrients, including nitrogen (N), phosphorus (P) and potassium (K). This study investigated the relationship between soil nutrient levels and maize disease occurrences in the Mopani District Municipality, Limpopo Province, South Africa. Soil and maize leaves were collected using a systematic sampling approach. Grids of 10 × 10 m were created, covering a maize field. Forty soil samples were collected a day before the planting date and sent to the laboratory for analysis of N, P and K. During the tasseling stage of the maize plant, 40 maize leaf samples were collected and sent to the laboratory for disease identification. Maize leaves were classified as healthy, southern corn leaf blight (*Bipolaris maydis*), northern corn leaf blight (*Exserohilum turcicum*), maize streak disease (Maize streak virus), nitrogen-deficient or phosphorus-deficient. Generalized Linear Models (GLMs) with a corrected Akaike Information Criterion (AICc) showed a significant relationship between low soil nutrient levels of N, P and K and maize disease occurrence ($p < 0.0001$). The interaction of the N*P*K model had the lowest AIC value (AICc = 28.53), indicating the necessity of considering synergistic effects in maize disease management. All the model performances had a delta AICc = 0. These findings highlight the significance of comprehensive soil management strategies in enhancing the disease resistance, well-being and yields of maize crops.

Keywords: maize diseases; soil nutrients; disease detection; smallholder farmers; AICc analysis

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1. Introduction

Maize is the most essential cereal crop across the globe after rice and wheat [1]. It is a staple food for billions of people worldwide, serving as a key source of carbohydrates due to its rich composition, mainly in the form of starch, and has proteins, lipids, vitamins and minerals [2]. In the African continent, maize is the most cultivated crop with the highest total grain yield [3,4]. In regions such as Sub-Saharan Africa, maize is the most important agricultural species, producing nearly 30% of the caloric intake of the population. However, the maize crop is susceptible to a wide range of diseases such as maize streak virus [5], pests such as maize weevils [6] and abiotic stresses such drought [7], which can significantly impact yield and quality. The majority of maize producers in SSA and South Africa are smallholder farmers who depend on agricultural production for their livelihoods [8]. These farmers are mostly unequipped for disease identification and management.

Approximately 50% of the population grows maize in Sub-Saharan Africa (SSA) [9], where the interplay of biotic and abiotic factors is known to cause up to 80% of maize yield losses [10,11]. Amongst producers, smallholder farmers face the most challenges, including, inter alia, pest infestations, disease outbreaks, unpredictable weather patterns and market fluctuations, which are the primary drivers of poverty and income instability in these farming communities [12]. With limited resources, smallholder farmers struggle to adequately manage the above risks effectively [13]. The maize crop requires a balanced intake of essential nutrients to maintain its growth, development and natural defense mechanisms [14]. Sufficient nutrient availability during crop growth is crucial to tackle disease damage in plants [15]. Nutrient deficiency leads to weak growth, compromising their ability to fend off pathogens. To overcome this, agriculture needs to move beyond just the emphasis on production and encompass improved crop health. It is essential to find alternative ways to control maize diseases that do not affect the environment or product quality [16].

Managing soil health is crucial for improving crop yields, preserving biodiversity and ensuring the land's long-term productivity. Crop health highlights the complex relationships between soil organisms and crops [17] in symbiotic association, amongst others, which directly impact disease and pest control [18]. Nutrient supply is the most prominent aspect that influences soil health. The nature and properties of nutrients supplied determine the flow and recirculation of essential elements within the soil system [19,20]. Soil nutrients such as N, P and K are necessary for maize crop growth and production [21]. A deficiency in the interplay of these nutrients in physiological processes can have negative effects on the production and quality of maize crops [22].

In Sub-Saharan Africa, maize production is primarily affected by diseases, including maize streak diseases (maize streak virus) and northern corn leaf blight (*Exserohilum turcicum*) [23–25]. These diseases are endemic in the region, and their manifestations are less predictable due to their high dependence on weather and climate variability [26]. Northern corn leaf blight is a significant problem for maize production worldwide [26,27]. This disease is caused mainly by premature dryness in the leaves [28] and is capable of causing yield losses of up to 70% [29]. However, in Sub-Saharan Africa, maize streak has been reported to be a devastating disease that affects national economies due to yield losses, losses of income and increased maize prices [5]. There is little to no information about southern corn leaf blight in SSA.

Agricultural production has increased due to the availability and accessibility of improved nutrient supplies [30]. Yet, soil nutrient imbalance is not always the only cause of crop diseases and contributes indirectly to the overall health of crops. Agricultural production can be improved in many ways, including adapting to advanced technologies. Applying remote sensing and geographical information systems (GIS) has opened new possibilities for addressing challenges in managing the maize crop. Nevertheless, the advances in disease detection techniques using machine learning algorithms such as support vector machines have limitations in complex agricultural settings [31]. When data are limited, support vector machines are vulnerable to dimensionality issues and noisy and incorrectly labeled data [32]. In these cases, alternative methods can improve accuracy and reliability.

Maize diseases can be accurately detected and monitored using satellite imagery and spatial data over large areas [33]. Several studies have used remote sensing and GIS to distinguish maize diseases in the agricultural field. Zhang and Zhang [34] applied a new concept of Local Discriminant Projects (LDPs) as a strategy to describe and classify maize diseases and obtained an accuracy assessment of 94%. A multi-classifier approach with cluster analysis has been implemented to advance precision in detecting maize diseases, deriving adaptive weighting measures and achieving 94.71% accuracy [35]. Nevertheless, owing to the limited resilience exhibited by conventional support vector machines and analogous techniques [36], their efficiency has been constrained by complex agricultural settings. These settings can be characterized by various factors such as diverse crop types, varying soil conditions and pest management strategies. In this context, unraveling the complex relationship between soil nutrient profiles and maize diseases is paramount, which could offer practical insights into maintaining an optimal soil nutrition balance for farmers.

Although environmental conditions, natural hazards and climate change can lead to disease susceptibility in maize [37], soil nutrient imbalances have a stronger effect on disease occurrences, making crops vulnerable to pathogen attacks. Thus, there are no or few scientific findings on soil nutrient imbalances and leaf disease occurrences. Given the sophisticated interplay of soil properties and processes, assessing soil health is vital for detecting and monitoring crop diseases. Understanding the soil's physical, chemical and biological characteristics enables farmers to make informed decisions and implement sustainable practices to enhance soil health for better crop production.

This study aims to investigate the link between nutrients and disease occurrences and develop models for maize disease detection. Logistic regression was applied to predict and enhance the management of maize diseases by analyzing NPK nutrient levels. Logistic regression allows the assessment of the relationship between soil nutrient data and the likelihood of disease outbreaks. By employing logistic regression to analyze nutrient distribution patterns, it becomes possible to anticipate areas of the maize field that might be prone to diseases due to imbalanced soil nutrient levels. This approach enables interventions, such as adjusting fertilization strategies or implementing precision agriculture techniques, to mitigate disease risk.

2. Materials and Methods

2.1. Study Site

This study took place in the Mopani District Municipality (23°24′59.99″ S and 30°44′59.99″ E) in Limpopo Province, South Africa (Figure 1). The district is predominantly composed of rural areas and communities, featuring small-scale farms that specialize in low-yield production. These farms vary in size from 0.5 to 15 ha and are primarily used for personal consumption, with only a minor surplus for sale [38]. The Mopani District is located in a subtropical region where the temperatures remain consistently temperate annually [39], receiving an average annual rainfall of approximately 500 mm, most of which occurs during the summer months between October and March [40]. The fertile land in the district's western part supports a substantial amount of commercial farming [41,42]. The interplay of the subtropical climate, high temperatures all year and rainfall throughout the summer season creates a diverse environment that accommodates both natural vegetation and cultivated crops, supporting the livelihoods of rural communities [43].

2.2. Experimental Design

To thoroughly assess maize diseases, a systematic sampling method was utilized to design 40 polygons in a 10 × 10 m grid-sampling layout in a 0.8 ha maize field (Figure 2), strategically positioned to cover the entire study area. This systematic approach ensured a thorough and representative examination of the maize crop's health and disease conditions. The data collection included visual inspections, soil and maize leaf sampling and laboratory analyses, all chosen to ensure the accuracy and reliability of the results.

2.3. Soil Sampling

Soil samples were collected before the planting of maize on 3 March 2023. A total of 40 soil samples were collected in each 10 × 10 m grid at a depth of 10 cm since the study focused on the surface topsoil. This layer plays a crucial role in supporting maize plant growth and is directly involved in nutrient exchange and microbial activities [44]. To assess the soil's chemical content (N, K and P), the samples collected were sent to the Agricultural Research Council—Natural Resource and Engineering (ARC-NRE) Analytical Services Laboratory.

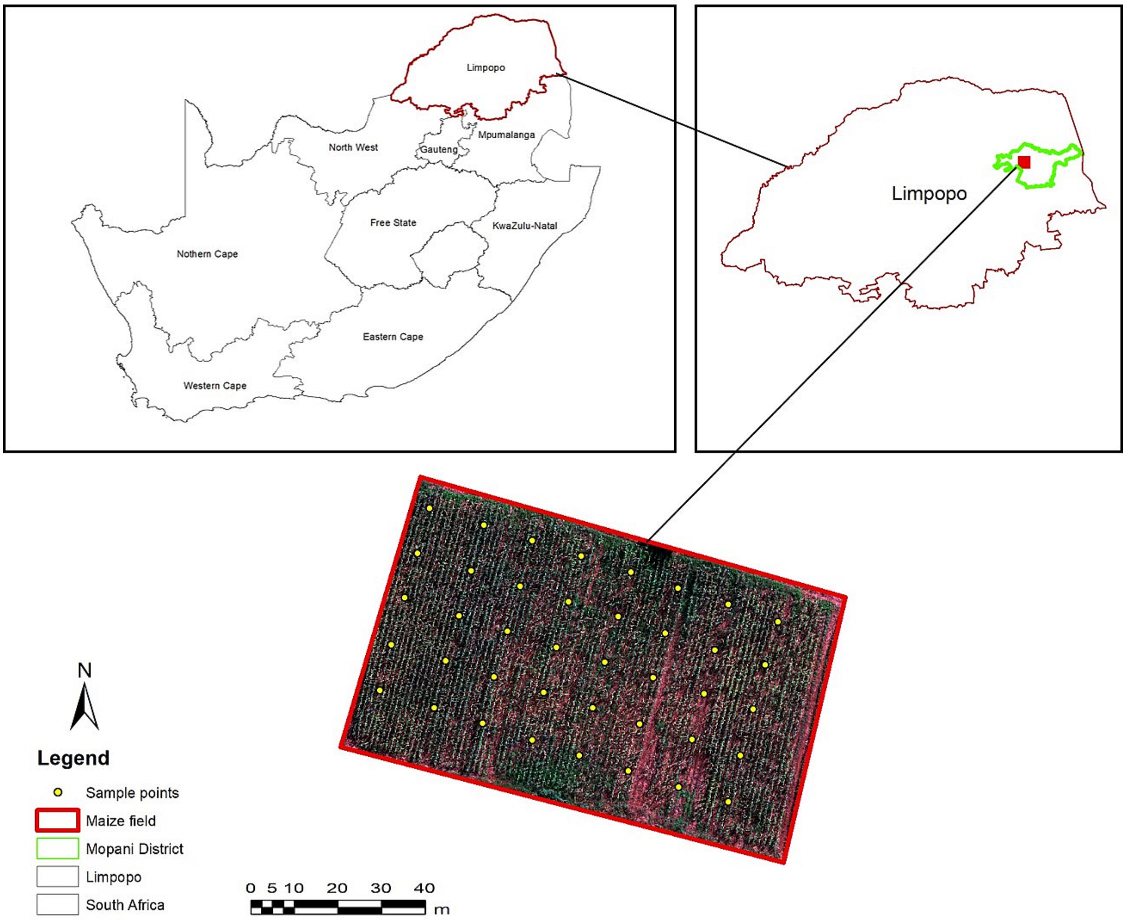

Figure 1. Study area map of maize field with sample points of soil nutrients in Mopani District, Limpopo Province, South Africa.

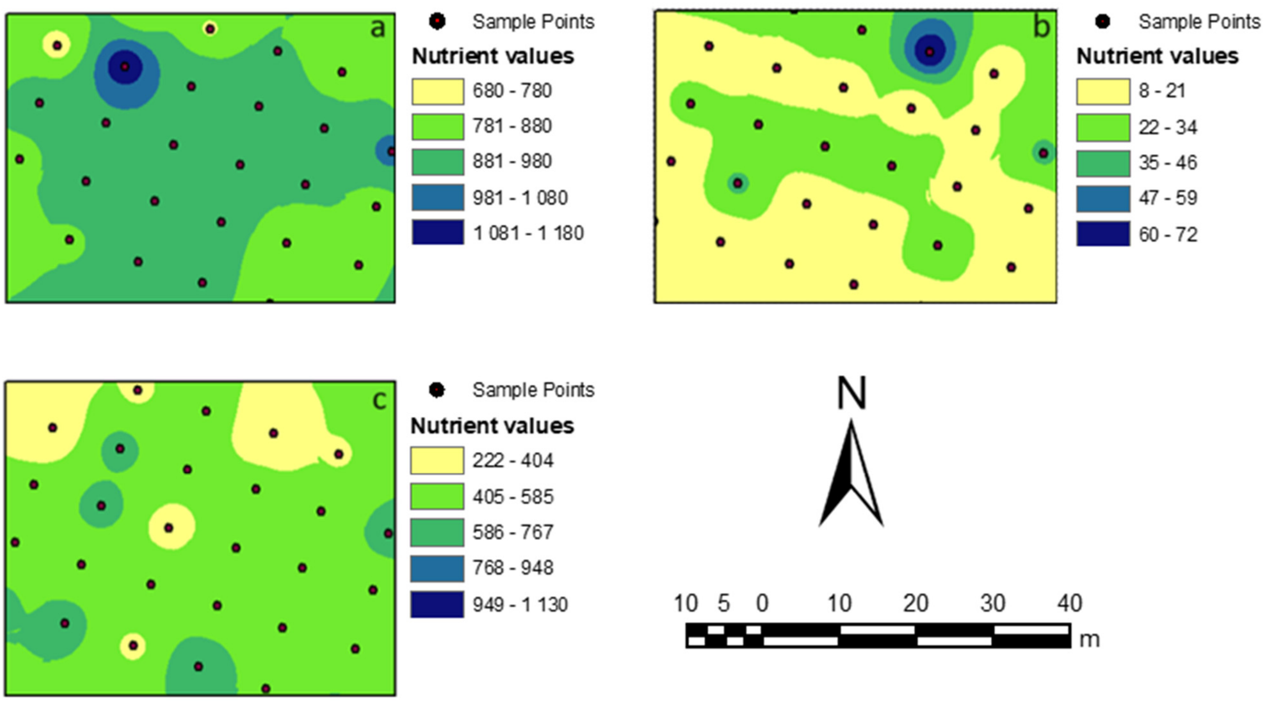

Figure 2. Geospatial distribution maps of soil nutrients: (**a**) nitrogen, (**b**) phosphorus, (**c**) potassium.

2.4. Maize Disease Data Collection

This study's primary data collection method entailed an on-site visual assessment of maize disease symptoms in the field. A total of 40 maize leaves were collected during the tasseling stage of maize growth on 5 May 2023, and the observed conditions were recorded, comprising both diseased and healthy maize crops. A binary classification system was adopted to facilitate analysis and interpretation, assigning a value of 0 to denote healthy maize crops and a value of 1 to indicate the presence of disease symptoms. Further analyses were carried out by the Agricultural Research Council (ARC) for disease identification.

2.5. Data Analysis

2.5.1. Statistical Analysis of the Effect of NPK Nutrients on Disease Occurrence

An analysis of variance (ANOVA) was conducted using JMP 17 PRO statistical software to investigate the influence of N, P and K levels on the occurrence of maize diseases. Mean separation was calculated using a Student's Test with a significance level set at $p < 0.05$.

2.5.2. Developing Models to Evaluate the Effect of NPK on Maize Disease Occurrence

A Generalized Linear Model (GLM) with a binomial link function was employed to investigate the relationships between soil nutrients and the presence of maize diseases. The analysis was conducted using the R software (R version 4.3.1 (16 June 2023)—"Beagle Scouts" ©2023 the R Foundation for Statistical Computing). The investigation specifically aimed to evaluate the associations of individual N, P and K nutrients on the presence of maize diseases. GLMs were built using single variables, additive effects and the interactions of the same variables of N, P and K.

Generalized Linear Models (GLMs) were constructed utilizing step-down procedures [45]. The Akaike Information Criterion corrected for small sample sizes (AICc) was used to evaluate the relative fit of the models, balancing goodness of fit with model complexity, where lower AICc values indicated better-fitting models [46]. AICc provides a more appropriate measure of model fit, mainly when dealing with small sample sizes [47]. The delta AICc was employed to measure the contribution of each predictor variable, offering valuable insights into the significance of individual indices in explaining disease occurrences [48]. The AIC-guided model selection process played a crucial role in determining the most suitable model, serving as a benchmark for comparing the merits of each model [46]. Models with delta AICc values < 2 were considered equally well fitted, indicating comparable explanations of the data [46].

3. Results

Maize leaf condition analyses revealed six distinct categories, including healthy, southern corn leaf blight (SCLB), northern corn leaf blight (NCLB), nitrogen deficiency, phosphorus deficiency and maize streak disease (Figure 3). Healthy maize leaves showed uniform pigmentation and structure with no damage in the leaf. SCBL was identified with necrotic lesions along the leaf, while NCBL had elongated lesions concentrated between the veins of the leaf. Nitrogen deficiency displayed yellowing discoloration starting at the tip and continuing along the midrib of the leaf. Phosphorus deficiency manifested a purplish discoloration along the leaf edges. Maize streak disease was marked by the presence of fine, chlorotic streaks along the veins of the leaf.

Healthy crops showed mean levels of 906.25 kg/ha for N, 459.63 kg/ha for K and 16.89 kg/ha for P (Figure 4). Crops with southern corn leaf blight showed slightly lower N (905 kg/ha) and K (499.5 kg/ha) levels, but a slight increase in P (18.25 kg/ha) content. Crops affected by the maize streak virus showed a decrease in N (883.33 kg/ha) and K (450 kg/ha) concentrations alongside lower P (13.19 kg/ha) levels compared to the healthy crops. Phosphorus deficiency displayed an increase in K (570 kg/ha) and P (19.97 kg/ha) levels but relatively stable nitrogen (879.29 kg/ha) content. Leaf blight showed increases in K (460.5 kg/ha), nitrogen (873 kg/ha) and P (28.72 kg/ha) concentrations. Conversely, nitrogen deficiency showed high N (630 kg/ha) and K (630 kg/ha) but stable P (17.41 kg/ha) levels compared to the healthy plants.

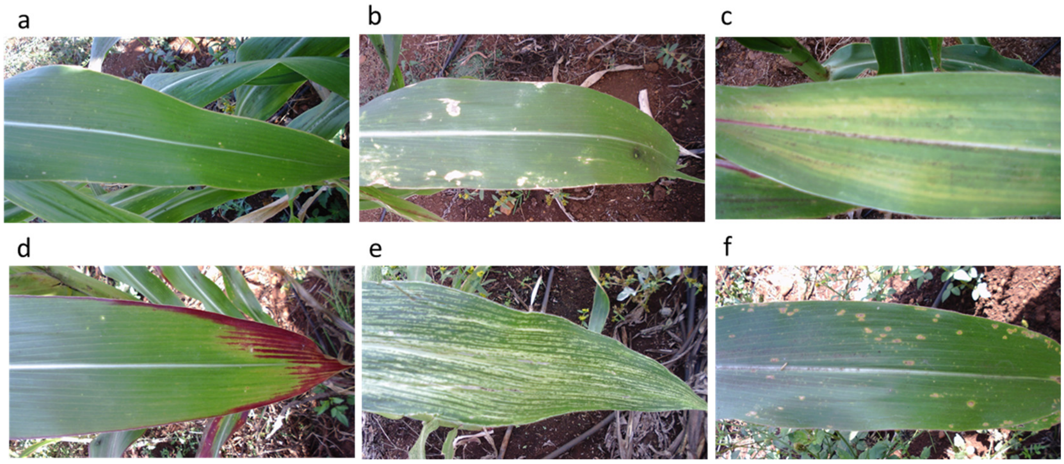

Figure 3. Conditions of maize leaves identified in the laboratory. (**a**) Healthy, (**b**) southern corn leaf blight (SCLB), (**c**) nitrogen deficiency, (**d**) phosphorus deficiency, (**e**) maize streak disease and (**f**) northern corn leaf blight (NCLB).

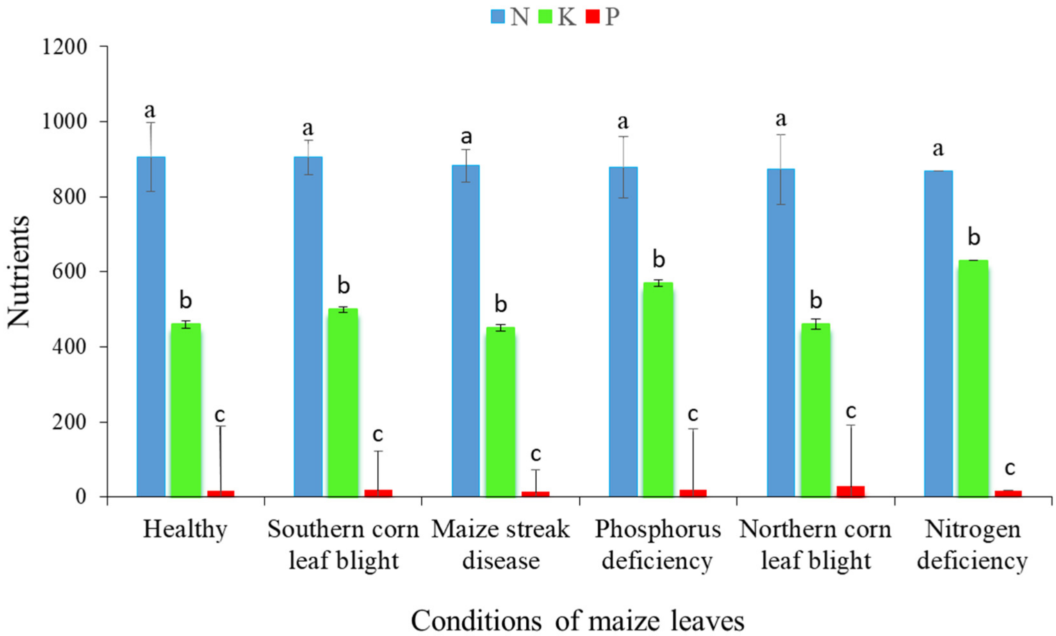

Figure 4. The mean values of N, P and K in relation to the six different maize health conditions identified in the maize field in Mopani District, Limpopo Province, South Africa: healthy, southern corn leaf blight, maize streak virus, phosphorus deficiency, northern corn leaf blight and nitrogen deficiency. Means were compared by JMP Pro software. NB: means were compared amongst the three NPK nutrients within each plant's health conditions. Different letters denote significant differences ($p < 0.05$; Student's Test).

The descriptive statistics highlighted the distribution and variability of N, P and K levels across the individual and combined variables (Table 1). Both the individual and combined variables are represented by the minimum, first quartile (1Q), median, third quartile (3Q) and maximum values. The minimum ranged from −2.4276 to −1.9051, while the maximum ranged from 0.805 to 1.53312. When considering the additive effects of variables (N + P, N + K and P + K), the displayed changing ranges and quartile distributions were shown. The interactions of NPK showed a wide range of values, with a minimum of −2.2877 and a maximum of 1.1761.

Table 1. Descriptive statistics of the single variables, additive effects and interactions of variables.

Variables	Min	1Q	Median	3Q	Max
N	−2.016	0.555	0.627	0.695	0.814
P	−2.102	0.449	0.626	0.739	0.805
K	−2.045	0.513	0.636	0.701	0.914
N + P + K	−2.187	0.258	0.443	0.758	1.133
N + P	−2.014	0.416	0.615	0.734	0.874
N + K	−1.965	0.385	0.537	0.718	1.053
P + K	−2.211	0.377	0.554	0.716	0.879
N*P*K	−2.288	0.001	0.011	0.186	1.176
N*P	−1.970	0.084	0.543	0.729	1.533
N*K	−1.905	0.203	0.490	0.616	1.195
P*K	−2.427	0.373	0.538	0.681	0.971

Note: 1Q: first quantile; 3Q: third quantile.

Various single-variable models were assessed for their goodness of fit based on their AICc values (Table 2). Phosphorus had the lowest AICc value of 43.24 with a delta AICc of 0, followed by potassium with an AICc value of 43.41 and a delta AICc of 0. Nitrogen had the highest AICc value of 43.81 with a delta AICc of 0.57.

Table 2. Comparative fit of alternative models relating to the occurrence of diseases in maize with single variables.

Variables	N	K	AICc	Delta AICc (Δi)
P	40	2	43.24	0
K	40	2	43.41	0.17
N	40	2	43.81	0.57

Note: N: sample size; K: number of parameters.

Across the models tested with additive effects (Table 3), the N + K model yielded the lowest AICc value (44.23) with a delta AICc of 0 and Akaike weights of 1, followed by P + K (AICc = 44.40), with a delta AICc of 17. The additive effects model showed the changing AICc and delta AICc values.

Table 3. Comparative fit of alternative models relating to the occurrence of diseases in maize with multiple variables.

Variables	N	K	AICc	Delta AICc (Δi)
N + K	40	3	44.23	0
P + K	40	3	44.40	0.17
N + P + K	40	4	44.90	0.67
N + P	40	3	44.99	0.76

Note: N: sample size; K: number of parameters.

The interactions of the N, P and K models showed the model with the lowest AICc value (Table 4). The interaction of N*P*K showed the lowest AICc value of 28.53 with a delta AICc of 0, followed by N*K (39.32), with a delta AICc of 10.79.

Table 4. Comparative fit of alternative models relating to the occurrence of diseases in maize with interaction variables.

Variables	N	K	AICc	Delta AICc (Δi)
N*P*K	40	4	28.53	0
N*K	40	3	39.32	10.79
N*P	40	3	43.55	15.02
P*K	40	3	44.60	16.07

Note: N: sample size; K: number of parameters.

4. Discussion

This study aimed to link soil nutrients (N, P and K) and the occurrence of diseases to develop models to detect diseases in maize crops in Mopani District, Limpopo Province, South Africa. The results showed that the best-fit model to detect maize diseases was found in the interaction of NPK, which obtained the lowest AICc value compared to those in the single-variable, additive effect and interaction of variables models. This highlighted the importance of balanced soil nutrition for crop disease resistance. The results are consistent with the findings of Fageria et al. [30], who indicated the important role of soil health and nutrient balance in improving crop production and minimizing disease occurrence.

The statistical analysis revealed intriguing insights into the distribution of soil nutrient concentrations throughout the field, providing a spatial comparison of variables. It illustrated how these values fluctuate in relation to identified diseases. Notably, nitrogen (N) exhibited the highest variability among maize diseases, closely followed by potassium (K). Surprisingly, the variability in phosphorus (P) was inconsistent across the field, suggesting complex dynamics at play. These results are consistent with the finding of Saidou et al. [49], who found high N, moderate K and low P when analyzing NPK intake for maize. This underscores the nuanced interplay between soil health and crop diseases, warranting further exploration and discussion.

The interplay between soil health and crop diseases revealed the distribution of soil nutrient concentrations throughout the field and provided a spatial comparison of different diseases. It demonstrated how nutrient levels fluctuate in relation to identified diseases (Figure 2). The severity of the diseases varied across the field. The spatial variability of soil nutrients generally caused heterogeneous symptoms of maize diseases due to different nutrient levels available for crop uptake. These results would be because of the relation between crop nutrition and phytopathogens [50].

The field observations revealed that there were many more diseased crops than healthy crops. Thus, managing crop nutrition impacts crop diseases [50–53]. Nitrogen is generally higher than phosphorus and potassium, which could impact maize health. According to Muller et al. [54], excessive nitrogen increases the plant's lushness, creating a favorable microclimate for fungal growth by prolonging leaf wetness. However, a deficiency in nitrogen weakens maize crops, increasing the possibilities of vulnerability to diseases infections such as NCLB, leading the crop to have thinner leaves with less chlorophyll content. Dordas [55] indicated that imbalances in soil nutrients reduce the effectiveness of the maize crop's defense responses. According to Zinsou et al. [50], only balanced nutrition with optimum levels of each nutrient could lead to the reduction in a disease.

The performance of the statistical modeling of N, P and K as single variables, additive effects and interactions of variables produced nuanced results that indicate the complicated relationship between soil nutrient levels and their impact on maize disease occurrence. The wide range and varying quartile distributions of deviance residuals across different nutrient variables indicate heterogeneity in the impact of these nutrients on maize disease occurrence. These results are consistent with a previous study that investigated the nature of nutrient–soil interactions and their effects on plant health [56]. The wider range of interactions in the N*P*K model indicates a strong match among the NPK variables, which has been well documented in the literature [57,58].

The additive effects of the N + K model outperformed those that employed a single-variable model. This is supported by lower values of the Akaike Information Criterion (AIC) and higher Akaike weights, which indicate that they fit the data better and explain more variation in maize disease occurrence than single-variable models. This implies that the addition of variables impacts maize disease detection and that the balance of multiple variables determines the nutritional condition and the resilience of maize crops. A similar study conducted by Vitousek et al. [59] highlighted the role of multiple nutrient deficiencies in affecting plant health and productivity.

5. Conclusions

This study revealed the complex relationship between the soil nutrients N, P and K and the occurrence of diseases in maize. The findings underscored the necessity of maintaining a balanced NPK profile for soil to promote optimal crop growth and production. Models considering the interactions of N*P*K demonstrated a better fit, suggesting the best interaction play effect in monitoring maize health dynamics. The findings demonstrate that imbalances in NPK levels contribute to detecting maize diseases caused by soil nutrient imbalances. This highlights the value of nutrient management in disease prevention. This study advocates for the implementation of soil nutrient management practices in the mitigation of crop disease risks.

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