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Research Paper

Developing models to detect maize diseases using spectral vegetation indices derived from spectral signatures

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ABSTRACT

Maize, a vital global crop, faces numerous challenges, including outbreaks. This study explores the use of spectral vegetation indices for the early detection of maize diseases in individual leaves based on crop phenology at the vegetative, tasselling, and maturity stages. The research was conducted in rural areas of Giyani in the Limpopo province, South Africa, where smallholder farmers heavily rely on maize production for sustenance. Fungal and viral diseases pose significant threats to maize crops, necessitating precise and timely disease detection methods. Hyperspectral remote sensing, with its ability to capture detailed spectral information, offers a promising solution. The study analysed spectral reflectance data collected from healthy and diseased maize leaves. Various vegetation indices derived from spectral signatures, including the Normalized difference vegetation index (NDVI), Anthocyanin Reflectance Index (ARI), photochemical Reflectance Index (PRI), and Carotenoid Reflectance Index (CRI) were investigated for their ability to show disease-related spectral variations. The results indicated that during the tasselling stage, the spectral differences had minimum absorption in the blue region. However, a distinct shift in spectral reflectance was observed during the vegetative stage with 70 % increase in reflectance. First derivative reflectance analysis revealed peaks at approximately 715 nm and 722 nm, which were useful in the discrimination of the different growth stages. Generalized Linear Models (GLM) with binomial link functions and Akaike Information Criterion (AIC) showed that individual vegetation indices performed equally well. NDVI ($P<0.001$) and CRI ($P<0.000$) showed the lowest AIC values across all growth stages, suggesting their potential as effective disease indicators. These findings underscores the significance of employing remote sensing technology and spectral analysis as essential tools in the endeavours to tackle the difficulties encountered by maize growers, especially those operating small-scale farms, and to advance sustainable farming practices and ensure food security.

1. Introduction

Maize (*Zea maize)* is the most cultivated crop across the world (Dowswell, 2019). It is known to produce variety of products such as flour, cereal, maize meal, and oil, which are not only consumed locally but also exported and consumed worldwide (Erenstein et al., 2022). The importance of maize in agriculture and disease outbreaks faced by the smallholder farmers in conjunction with climate change highlights the need for efforts towards adaptation and resilience (Laichena et al., 2022). Innovative agricultural practices improve livelihoods of farmers and contribute to food security, poverty reduction, and sustainable development.

The majority of the people in South Africa rely heavily on maize as a staple food for human consumption and as a source of feed for livestock. The country is mostly rural areas that prioritize agriculture as the primary activity, making maize production a critical part of the economy and food security (Biénabe and Vermeulen, 2011). Most of the maize production is dependent on rainfall, making it more vulnerable to the

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influences of climate variability and extreme weather events (Praveen and Sharma, 2019). Natural factors such as drought, floods, heatwaves, and diseases pose a considerable threat to maize production (Duchenne-Moutien and Neetoo, 2021).

Despite playing an important role in agriculture, smallholder farms face various challenges. Some of the challenges they encounter includes pest and disease outbreaks, extreme weather events, and market shocks, which promote poverty and income insecurity (Harvey et al., 2014). Due to limited resources and access to advanced technologies, these vulnerable farmers struggle to cope with such risks (Hertel and Rosch, 2010), and their livelihoods are impacted when agricultural production is reduced. The effects of reduced agricultural productivity extend far beyond economic concerns. It also directly affects food security, nutrition, income, and the farmers' well-being (Baiphethi and Jacobs, 2009). These challenges compromise the farmers' well-being as it is fundamentally tied to their health. Thus, it is of importance to address these challenges to promote sustainable development and poverty alleviation.

Crop diseases occur in smallholder farms in many ways due to changing weather and climate conditions. Fungal diseases become gradually dominant and destructive as weather pattern changes, creating favourable environments for diseases (Sibiya, 2009; Lamichhane and Venturi, 2015). Furthermore, there are 67 viruses identified as affecting maize crops (Redinbaugh and Zambrano, 2014). Disease detection is crucial and timely management strategies are urgently required. Redinbaugh and Zambrano (2014) showed that old plants tend to turn purple or reddish in the leaves and dwarfing is common when diseases infect plants in the early development stages. Accurate information about their location, extent, and severity is important to effectively fight these diseases and mitigate their influence (Zhang et al., 2019). Furthermore, details on disease distribution is of importance to guide suitable crop protection measures. The understanding of the scope of infections enable farmers to implement targeted and effective strategies, such as adjusting planting times, or using fungicides and pesticides carefully.

The traditional monitoring of such crop disease infection with the naked eyes may lead to inaccurate diagnosis (Ahila Priyadharshini et al., 2019). In contrast, hyperspectral remote sensing provides non-destructive ground information for detecting and monitoring crop diseases (Shi et al., 2017). These sensors serve as evolutional approach in agricultural management. These sensors produce high quality images with spatial and spectral resolution, which are suitable for detailed and accurate crop monitoring (Ghamisi et al., 2017). This includes discrimination of vegetation at species level and detection of plant physiology to determine plant health status (Susič et al., 2018). Hyperspectral remote sensing consists of hundreds of narrow intervals of spectral bands (Ranjitha and Srinivasan, 2014), that provide information such as stress conditions and it is very crucial in crop disease management. The technique of detecting healthy and diseased crops can be done focusing on a number of key wavelengths in the spectrum and those that use the entire spectrum response.

Remote sensing has been proven to be a valuable tool for crop disease detection at the leaf and canopy levels (Herrmann et al., 2018; Zheng et al. 2018). In detecting Fusarium virguliforme from soybean, Herrmann et al. (2018) using canopy and leaf spectral data found classification accuracies of 88 % and 91 % for calibration, 79 % and 87 % for cross-validation, and 82 % and 92 % for validation respectively. To enhance the accuracy and sensitivity of plant reflectance measurements and mitigate the impact of background interference, researchers use vegetation indices. Vegetation indices that combine sensitive bands in a specific mathematical form can improve plant parameter reflectance sensitivity and reduce the effects of various types of background interference (Zheng et al., 2010). In the past few years, researchers have put forth and explored different vegetation indices for various specific purposes (Bolton and Friedl, 2013; Gao et al., 2020). These purposes include pinpointing, measuring, or distinguishing issues such as water stress, diseases, pests, and nutritional deficiencies in plants. Several of these indices are seen as applicable to identifying plant diseases because when plants undergo physiological stress, it results in alterations to their pigment composition, such as carotenoid, chlorophyll, and xanthophyll, which are detailed in Table 1.

Notably, these indices can be used to estimate crop yield (Panda et al., 2010), detect leaf area index variations (Brantley et al., 2011), and identify crop diseases (Huang et al., 2014). Several spectral indices derived from the literature have shown promise for detecting plant diseases. Huang et al. (2014) found that the photochemical reflectance index (PRI) was strongly correlated with the yellow rust disease index in wheat. Furthermore, Devadas et al. (2009) found that the anthocyanin reflectance index (ARI) demonstrated promising capabilities in distinguishing between yellow rust-infected wheat and healthy wheat, as well as wheat affected by other rust diseases.

Currently, no study has quantified the ability of spectral indices to discriminate healthy versus diseased plants using the crop of maize. This study aimed at developing models for detecting maize diseases using spectral indices derived from spectral signatures of the different crop

Table 1
Spectral reflectance indices used for the description of disease of stress in crops as derived from a detailed literature survey.

Spectral Indices	Define	Formula	Reference
Normalized difference vegetation index (NDVI)	The NIR (Near-Infrared) and Red bands encompass wide spectral ranges, spanning from 775 to 825 nm for NIR and from 650 to 700 nm for Red, effectively covering the majority of essential pigments.	(P800 – P680)/(P800 + P680)	Rouse et al. (1974)
Anthocyanin Reflectance Index (ARI)	Anthocyanin accumulation is initiated by factors such as strong light, UV-B radiation exposure, low temperatures, arid environmental conditions, physical damage, bacterial and fungal infections, and deficiencies in nitrogen and phosphorus. To gauge the presence of anthocyanin in both healthy aging leaves and leaves experiencing stress, an Anthocyanin Reflectance Index (ARI) has been proposed as a potential assessment tool.	(1/P550)-(1/P700)/P800)/(1/P550)-(1/P700)	Gitelson et al., 2002
photochemical Reflectance Index (PRI)	R531 is associated with the condition of the xanthophyll cycle, and because xanthophyll pigments function as a defense mechanism against excessive light, they have a pivotal role in enhancing the effectiveness of light utilization (LUE). As a result, increased xanthophyll activity is linked to elevated stress levels, which in turn lead to a decrease in light utilization efficiency (reduced LUE).	(P531-P570)/(P531 + 570)	Gamon et al., 1992
Carotenoid Reflectance Index (CRI)	Utilized for the determination of the carotenoid-to-chlorophyll-a ratio.	(1/P510)-(1/P550)/(1/P510)-(1/P700)	Steddom et al. (2003)

phenological stages focusing on the vegetative, tasseling and maturity stages.

2. Study area

The study was conducted in Giyani (23°24′59.99″ S 30°44′59.99″ E) in Mopani District of the Limpopo Province, South Africa (Fig. 1). Small-scale farms are mainly located in the rural areas and are characterised by low production and small sizes that range from 0.5 to 15 ha, produced primarily for personal use and with little marketable surplus (Cousins, 2010). The soil is mainly basalt, sandstone, and biotite gneiss, and generally has low endemic soil fertility. Mopani District is in a sub-tropical region with warm temperatures all year round (Fitchett et al., 2016), receiving an average of 500 mm annual rainfall during summer between October and March. The large portion of Mopani District Municipality consist of rural communities under subsistence livelihood. The western part of the district is abundant in fertile land, making it conducive for large-scale commercial agriculture (Nembilwi et al., 2021). The cultivated land and residential areas are located in the western half of the district, with woodlands and grasslands in the east. Despite the dry and drought-prone agro ecology, maize is the predominant grain in most districts.

3. Data and methods

3.1. Data acquisition and processing

The study was conducted in Giyani from April 2023 to June 2023 and focused on three distinct phenological stages of maize crop, namely the vegetative, the tasselling, and the maturity stages. In order to conduct a comprehensive evaluations of the crops, a systematic sampling approach was employed. A total of 36 data points were collected from a carefully designed 10 x 10 m systematically grid-sampling scheme, strategically placed to cover the entirety of the study area at each of the specified growth stages. This approach allowed for a representative and comprehensive analysis of the health and disease prevalence in the maize fields under examination. The methods used in this study, which are detailed in Fig. 2, were critical in achieving the study objectives. These methods encompassed a range of techniques, including but not limited to visual inspection, laboratory analysis, and data collection tools. Each method was selected and implemented to ensure the accuracy and reliability of the findings, ultimately contributing valuable insights into the health and disease dynamics within the maize crops during these crucial growth stages.

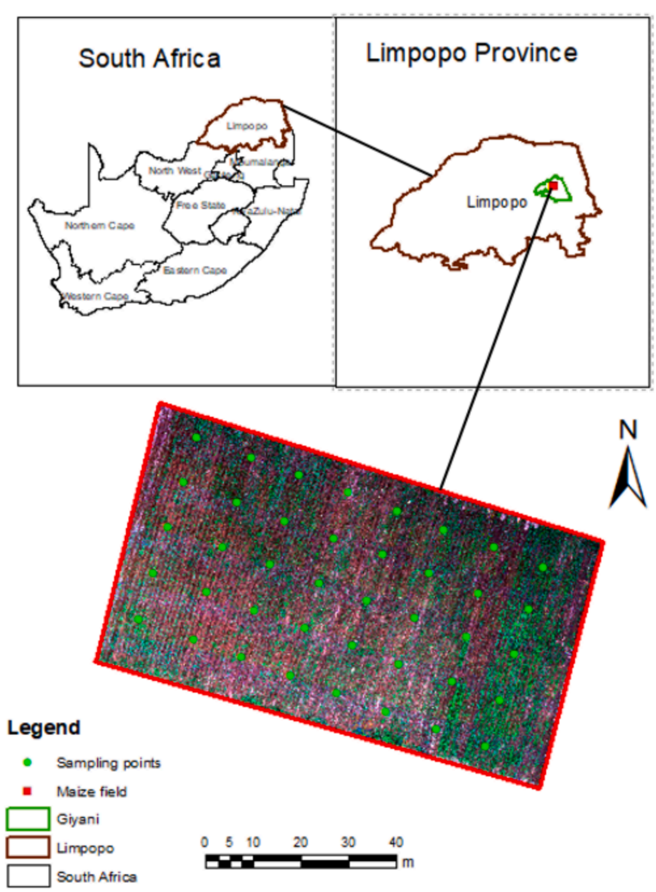

Fig. 1. Mopani district and the field selected for maize study in Limpopo, South Africa.

Spectral reflectance were collected using spectroradiometer (ASD Inc., Boulder, CO, USA) FieldSpec®3 spectrometer. Maize leaves were first inspected with visual observation for any potential disease symptoms. Spectral signatures of both diseased and healthy crops were recorded. The spectra reflectance was taken during sunny and clear-sky, which gives interpretability of reflectance as opposed to the radiance reflected by a given object . The spectroradiometer used in the field contains the wavelength ranging from 350 to 2500 nm (ASD, 2005), enabling to capture a wide-range of spectrum information. Referencing panel was used to calibrating the ASD instrument during the data collection (Labsphere North Sutton, NH, USA). White reference measurements were taken every five minutes for precision and accuracy. The reflectance spectra were analysed using View Spec Pro software (Analytical Spectral Devices, Inc.).

3.2. Data analysis

3.2.1. Spectral reflectance measurements using ASD

The spectroradiometer is an invaluable tool which accurately takes and records five spectral measurements for each sampling location, so these measurements could be further averaged to mitigate the impact of the instrumental and environment noise (Zhang et al., 2011). The atmospheric water absorption waveband located at 350–400 nm, 1350–1450 nm and 1800–1900 nm were removed from analysis (Wei et al., 2017). After this initial data processing step, spectral indices were collected for each growth stages of maize. The main focus was to collect spectral signatures of healthy and diseased maize crops at the canopy level, then extract vegetation indices at each growth stages. Vegetation indices including the Normalized Difference Vegetation Index (NDVI), the Anthocyanin Reflectance Index (ARI), the Photochemical Reflectance Index (PRI) and the Carotenoid Reflectance Index (CRI) to evaluate the levels of carotenoid pigments within the maize leaves, were used to examine the properties of crops.

3.2.2. Developing models for detecting maize diseases

The Generalized Linear Model (GLM) approach with a binomial link function, utilizing the R software (R version 4.3.1 (2023–06-16) –- "Beagle Scouts" ©2023 the R Foundation for Statistical Computing) was used to build models using vegetation indices. This statistical approach enabled the exploration of the relationships between disease detection and spectral indices (NDVI, ARI, PRI, and CRI), across all three growth stages of maize. This aim was to assess the ability of the spectral indices to discriminate maize diseases at each specific growth stage. For model building and selection, step-down procedures were implemented and the Akaike Information Criterion (AIC) was used evaluate the fit of the models.

Each model was evaluated based on the residual deviance statistic to gauge the contribution of each predictor variable. The AIC model selection process played an important role in guiding our model choice, serving as a measure for comparing the relative support of each individual model. Models with delta AIC values < 2 were considered equally well fitted, implying that they provided comparable explanations of the

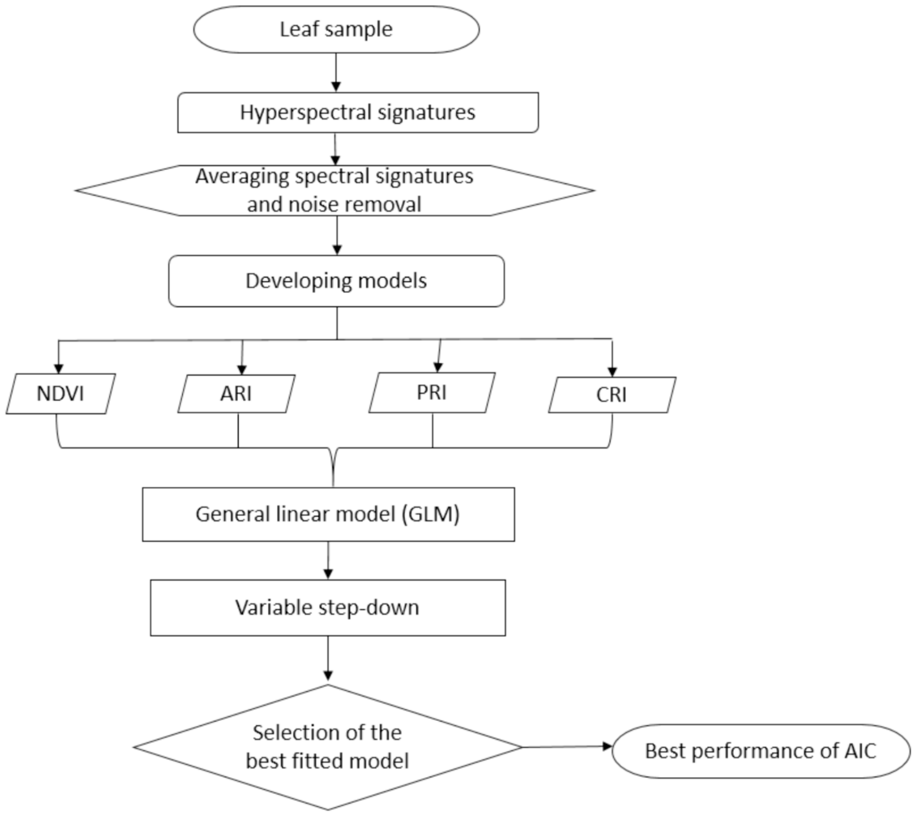

Fig. 2. Flowchart of the methodology used to develop the models for maize diseases detection with existing spectral indices.

data. In cases where multiple models exhibited delta AIC values < 2, our decision-making process favoured the model with the fewest parameters, in line with principles of model parsimony and simplicity, as the most appropriate choice. This comprehensive analytical framework enabled us to understanding the relationships between spectral indices and maize diseases across various growth stages.

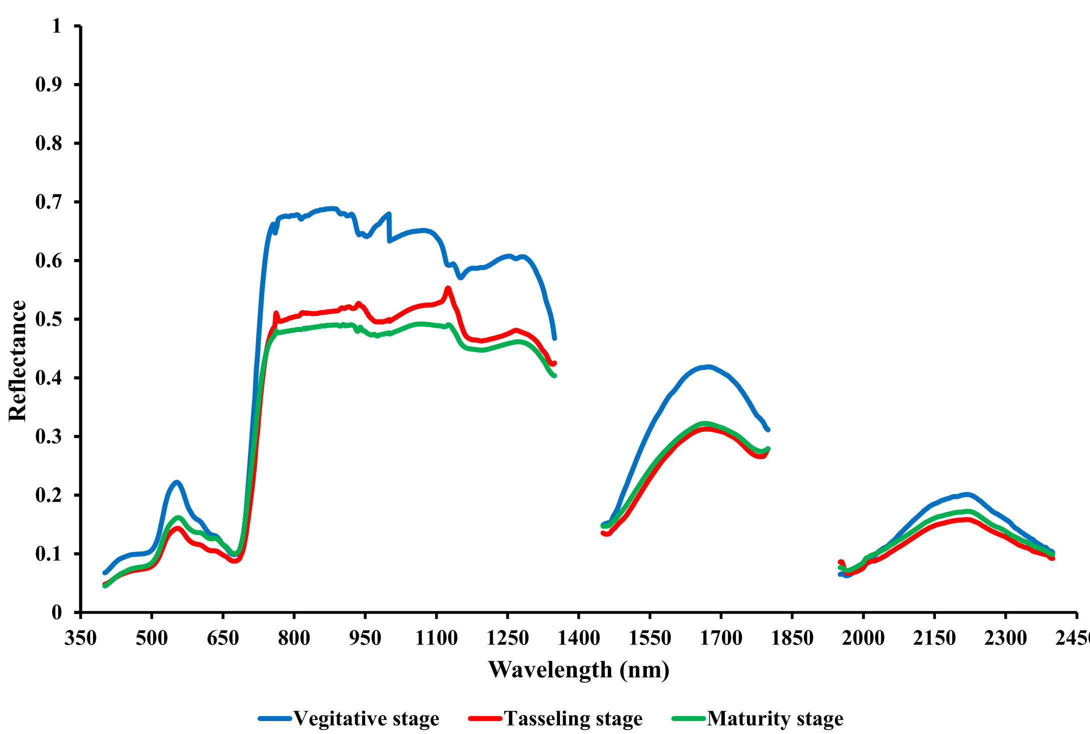

Fig. 3. Spectral reflectance of different phenological stages of maize crops in Giyani.

4. Results

4.1. Spectral analysis of healthy and diseased maize

The spectral reflectance in the chlorophyll region of the spectrum differs according to the crop health status and the farm management-condition used. The pattern of the spectral signature for the vegetative, tasselling and maturity stages were similar (Fig. 3). The spectral signature of the maize crop during tasselling stage showed the highest absorption in the red band around 670 nm of wavelength in the electromagnetic spectrum followed by vegetative and maturity stages. However, the vegetative stage showed the highest spectral reflectance of 70 %.

The patterns of the overlapping spectral signatures obtained from the three different phenostages, were further teased into a first derivative curve, showing a conspicuous peaks at 715 and 722 nm wavelengths for the first and the second peaks, respectively (Fig. 4). The pattern of the first derivate is more explained and different in the vegetative stage with the highest peaks shown. The tasselling stage, followed by maturity stage showed a shift to the longer wavelengths.

4.2. Developing models to predict maize diseases

The pattern of reflectance of the spectral indices differ according to the growth stages (Fig. 5). However, Vegetative and tasselling stages showed similar patterns where CRI had the highest reflectance, followed by NDVI and PRI. The reflectance of ARI was the lowest. Moreover, the maturity stage had a different pattern with the highest reflection in CRI, followed by ARI and NDVI. The PRI reflectance was the lowest. The spectral reflectance of maize crops showed significant differences between the spectral indices (P<0.000) regardless of the growing stages.

The spectral indices varied amongst the growth staged of maize, thus, their model performance differ. During vegetation stage, the IAC values ranged from 28.86 to 31.09 (Table 2). The single variable models showed the IAC values compared to the multiple variable model. ARI had the lowest AIC value of 28.86, followed by NDVI with 29.12 AIC value. All models had Delta AIC of 1 and the alike weights (wi) of 1.

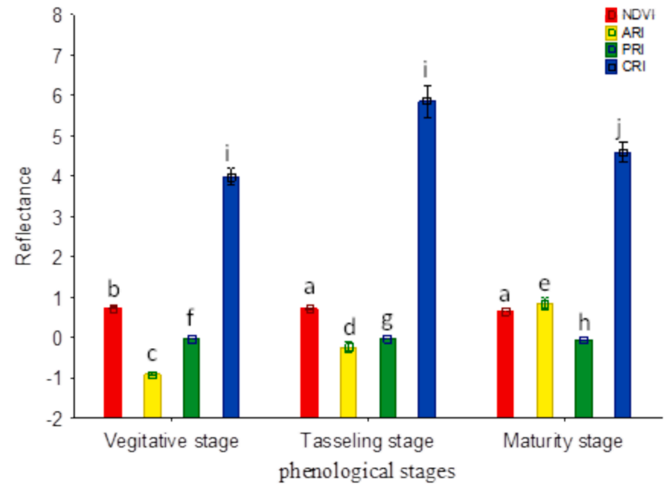

Fig. 5. The vegetation indices extracted from the spectral signatures of maize: NDVI (a-b), ARI (c-e), PRI (f-h) and CRI (i-j) during the vegetative, tasselling and maturity stages of maize. Means were related by one-way ANOVA and those followed by the same letter(s) are not significantly different ($p > 0.05$; Fisher LSD test).

Table 2
Comparative fit of alternative models relating to the occurrence of diseases in maize during the vegetative stage of growing.

Models	Sample size	K	AIC	Delta AIC(Δi)	Akaike weight(wi)
ARI	36	1	28.86	0	1
CRI	36	1	29.10	0	1
PRI	36	1	29.11	0	1
NDVI	36	1	29.12	0	1
ARI+CRI	36	2	30.08	0	1
ARI+PRI	36	2	30.84	0	1
PRI+CRI	36	2	31.09	0	1

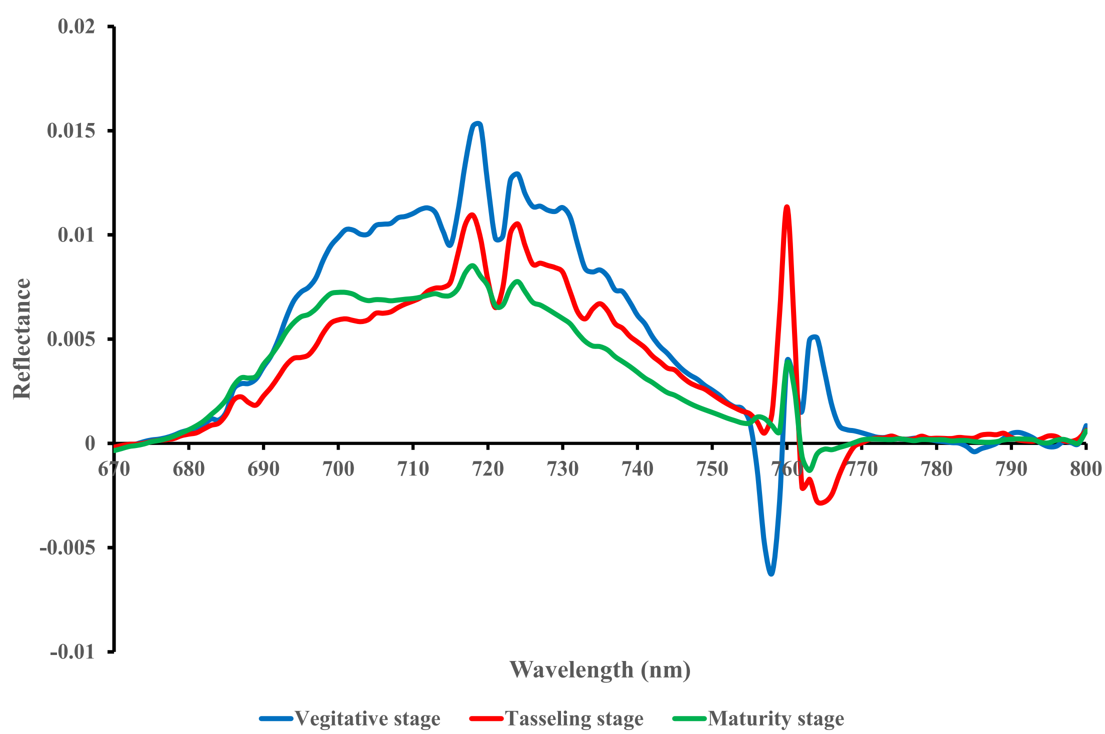

Fig. 4. First derivative curves of different phenological stages of maize crops in Giyani.

Multiple variable models did not show an influence in improving the model AIC values from the single variables.

During the tasselling stage, the model performance decrease with increasing AIC values ranging from 58.41 to 60.39 (Table 3). The best performed model for tasselling was with the single variable CRI (58.41 AIC value), followed by NDVI with AIC value of 58.52. The models in this stage has poor performance compared to the vegetative stage. The performance of the models among the single variable and multiple variable are more comparable as their AIC values are more close to each other.

The results shows that the multiple variable carried the same Akaike weights as those of the single variable (Table 4). During the maturity stage, the models outperformed those from vegetative and tasseling stages with the lowest AIC values ranging from 4 to 14.9. The best performance was found from NDVI and ARI+CIR with AIC values of 4 and 6 respectively. The performance of both single variables and multiple variables models during the maturity stage suggest that they are potentially the best-fitting models among the three growing stages. Thus, all the models carried the delta AIC of 0 and the Akaike weights of 1.

5. Discussion

Crop disease detection is computationally fast and non-destructive (Mahlein et al., 2013; Bauriegel et al., 2011; Shirzadifar et al., 2020), which is important for effective crop management and the use of pesticides. The study developed models to detect maize diseases with vegetation indices derived from spectral signatures collected during three growing stages of maize (vegetative, tasseling and maturity). The examination of the spectral reflectance highlighted the valuable insights of both healthy and diseased maize of their growth cycle.

Spectral signatures of the diseased crop is mostly affected by the change in biochemical and biophysical content in a plant, which damages the leaf pigment and water content (Lillesand et al., 2008; Zhang et al., 2019; Adam et al., 2017). The influence of maize diseases were found in the visible (VIS) wavelength from 550 m to 700 nm and in the red-edge-NIR wavelength from 700 nm to 850 nm (Fig. 4). These spectrum regions are associated with chlorophyll content, leaf water content and leaf internal structure (Zheng et al., 2018). The observation in the vegetative and maturity stages revealed marginal difference in the reflectance patterns of healthy and diseased crops. Spectral reflectance patterns during the vegetative, tasseling, and maturity stages of maize followed similar pattern, however, there was a dense absorption in the blue region during the tasselling stage. This prominent slope in reflectance level serve as a potential indicator of crop health and disease vulnerability, which is consistent with previous study on spectral reflectance (Genc et al., 2013).

Examining the spectral reflectance from derivative curves revealed different variations in slopes within the 690–750 nm (Fig. 4). These differences in spectral characteristics shows the potential for the detection and monitoring of maize diseases at the canopy level using hyperspectral remote sensing data. However, the similarity in the patterns of the spectral reflectance curves of the three growing stages were challenging to differentiate. The first derivative analysis was employed and it was able to displayed two picks in the curves in order to distinguish between the three growing stages (Newete et al., 2014). The first derivative curve proved to be an effective strategy for distinguishing the spectral characteristics of maize crops among the three growing stages. The first derivative curve resembles that of the spectral reflectance. The similarity of the first derivative curve and that of the spectral reflectance validate the validate the effectiveness of the analytical approach employed in this study, supporting the idea that these peaks were meaningful indicators of the fundamental spectral characteristics associated with each growth stage.

Table 3
Comparative fit of alternative models relating to the occurrence of diseases in maize during the tasselling stage of growing.

Models	Sample size	K	AIC	Delta AIC(Δi)	Akaike weight(wi)
CRI	36	1	58.41	0	1
NDVI	36	1	58.52	0	1
PRI	36	1	60.16	0	1
PRI+CRI	36	2	60.21	0	1
ARI+CRI	36	2	60.34	0	1
ARI	36	1	60.39	0	1
ARI+PRI	36	2	62.07	0	1

Table 4
Comparative fit of alternative models relating to the occurrence of diseases in maize during the maturity stage of growing.

Models	Sample size	K	AIC	Delta AIC(Δi)	Akaike weight(wi)
NDVI	36	1	4	0	1
ARI+CRI	36	2	6	0	1
CRI	36	1	12.8	0	1
PRI+CRI	36	2	12.12	0	1
ARI	36	1	12.98	0	1
PRI	36	1	12.99	0	1
ARI+PRI	36	2	14.95	0	1

The analysis of spectral signatures across the three growing stages of maize revealed significant differences in the spectral indices (NDVI, ARI, PRI and CRI). The distinction of these spectral indices highlighted their potential as valuable tools for detecting and monitoring maize diseases (Abdulridha et al., 2023). The analysis imply that these spectral indices exhibit significant variation based on the growing stage. Such variations could indicate differing levels of stress or disease susceptibility within the crops. This findings are consistent with the previous research in spectral signatures across maize growing stages (Torres-Madronero et al., 2022). Furthermore, these spectral indices were used to develop models at each maize growing stages.

The development of GLM models performed differently based on the AIC values. The model performance during the maturity stage deemed to be the best-fiiting models with both Single and multiple indices having the lowest AIC values (Hu et al., 2023). This suggest that during maturity stage can be an optimal window for maize disease detection. The model performance was also assessed using the delta AIC and Akaike weights. Delta AIC was 0 for the models, indicating that there is no model within a category significantly outperformed the others. Moreover, the Akaike weights presents the likelihood of the model being the fitting model (Burnham and Anderson, 2002). The value of the Akaike weights was 1 in all the model, which shows that all models performed the same. The values of the delta AIC and the Akaike weight did not pose any challenge in choosing the best-fitting models due to the distinct AIC values of each models.

The best performance of the individual indices during vegetative stage shows that indicates that despite the additional predictors, the combination models do not provide a better fit to the data compared to the single predictor models. The study by Zheng et al. (2018) ARI and PRI as valuable indices for detecting crop diseases at the canopy scale respectively. Thus, during the tasselling stage, both single and multiple indices models had the highest AIC values compared to vegetative and maturity stages.

6. Conclusion

The outcome of the study highlighted the capacity of spectral analysis to differentiate between healthy and diseased crops during vegetative, tasseling and maturity stages of maize crops and the use of AIC analysis to assess the performance of the models. Timely and accurate disease detection crucial to crop health and yield, and beneficial to food security and livelihoods. The study findings have suggestions for improving crop disease detection with remote sensing in agricultural setting. The use of spectral indices deemed important in advancing the ability to calibrate satellite sensors when detecting and monitoring crop diseases. This study has highlighted the importance of adopting remote sensing and spectral analysis as essential instrument in the continuous researches to tackle the difficulties encountered in maize production.

CRediT authorship contribution statement

Basani Lammy Nkuna: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johannes George Chirima:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Formal analysis, Conceptualization. **Solomon W. Newete:** Writing – review & editing, Visualization, Validation, Supervision, Project administration. **Adolph Nyamugama:** Writing – review & editing, Visualization, Validation, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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