Maize Crop phenotyping for Disease resistance using UAV Multispectral data

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Abstract: Cost-effective and data-driven crop variety throughput phenotyping is critical for increasing yield in the face of climate change. Plant breeding programmes' success depend on development of high yielding crop varieties that are resistant to various biotic and abiotic threats. Rising temperatures and unpredictable rainfall patterns provides a conducive environment for the development of crop diseases. Maize is one of the main staple food crops in SSA, grown on a total of about 27 million ha according to FAO data. Adapting maize production to future climates depends not only on our ability to precisely predict future climate scenarios, but also on the development of robust adaptation strategies that address the challenges associated with climate change. These adaptation strategies include, but are not limited to, improved germplasm with resistance to diseases, and tolerance to heat and drought (Mutanga et al. 2017). In this regard, variety selection efficiency relies on accurate field-based phenotyping, which measures the relative genetic potential as influenced by the target production environment and expressed in terms of grain yield, biomass, and tolerance to abiotic and biotic stresses(Araus and Cairns 2014; White et al. 2012). With the proliferation of climate change driven plant diseases, the advent of Unmanned Aerial Systems has provided an opportunity to provide detailed and accurate crop phenotyping information.

This study explored the potential of UAVs multispectral data sets in improving the efficiency of crop phenotyping in maize (Zea mays L.) varietal response to the maize streak virus (MSV) disease. The study was conducted at Rattray Arnold Research Station (RARS) in Zimbabwe. The trial was planted on 23 November 2018 and the vegetative stage of the crop was in December 2018 and January 2019. A weather station was erected at the site to record all the required meteorological data. We evaluated three replicates of Twenty-five maize varieties grown in an experimental field trial under artificial MSV inoculation. Three established check varieties that represent resistant, moderate and susceptible sensitivity to MSV were selected. Fertilizer was applied at a rate of 450 kg ha-1 basal (13:26:13 – N: P: K) at planting with top dressing of 450kg ha-1 ammonium nitrate (34.5% N), split into (225kg ha-1) at early vegetative and the second half (225kg ha-1) at booting (pre-flowering) stage. Weed removal was conducted through hand pulling and herbicides application.

Scoring for the severity of MSV infection on a scale of 1 to 9 was done at mid-vegetative, flowering and mid-grain filling stages. Scale of 1 represented zero to very low susceptibility symptoms while 9 represented severe symptoms. The drone imagery was acquired using a Parrot Sequoia Multispectral camera mounted on eBee SQ UAV (Swiss Geo Consortium Sensefly, Cheseaux-Lausanne, Switzerland). The Parrot sequoia sensor is made up of 5 cameras, with 4 discreet bands: Green (530 – 570nm), Red (640 – 680nm), Red-edge (730 – 740nm) and NIR (770 – 810nm). An additional panchromatic band covering the red, green, and blue (RGB) is included. The UAV-derived multispectral reflectance data in the visible-NIR region were acquired at the three different phenological stages at an altitude of 42.5 m and a spatial resolution of 8 cm. Using Pix4Dmapper, the imagery was stitched and then input into QGIS to extract reflectance data. The bands for each variety were transformed into six indices, namely, the normalized difference vegetation index (NDVI), green normalized difference vegetation index (GNDVI), Rededge NDVI (NDVIrededge), Simple Ratio (SR), green Chlorophyll Index (CIgreen) and Rededge Chlorophyll Index (CIrededge).

Significant relationships were obtained between the indices and MSV scores with correlation coefficients ranging from 0.74-0.84. We further used the Random Forest (RF) algorithm to evaluate the utility of UAV-derived data in classifying varieties into resistant, moderately resistant and susceptible categories. The RF algorithm is robust and has some in-built functionalities that can be used to optimize variables, thus suitable in this case where one of the objectives was to rank the most important indices for phenotyping(Chemura et al. 2017; Pal 2005).

The optimized RF yielded overall classification accuracy of 77.3% (Kappa = 0.64) while the unoptimised RF yielded 68.2% (Kappa = 0.51) accuracy. The Mid-vegetative phenological stage was the optimal period for accurate varietal phenotyping and discrimination while the GNDVI, CIgreen, CIrededge and the Red band were the most important indices selected for improved classification.   Out of 30 variables used in the RF algorithm, only seven (including 5 VIs) were selected as optimal in classifying the different levels of infection levels. The selected bands and indices at vegetative stage were: CIgreen, GNDVI, CIred-edge, SR and NDVI, Red and Green

This study showed the importance of UAV-derived imagery in plant phenotyping, an encouraging result given the difficulties experienced in manual plat breeding phenotyping, which involves laborious screening of a large number varieties to select the most suitable ones for advancement and commercialization. The temporal analytical flavor adopted in this study provides an impetus to accurate phenotyping by taking advantages of the phenological information contained in different varieties in response to MSV infection. The result is critical for improved data provision at high spatial and temporal resolutions for plant breeding programmes, which will assist in the mitigation and adaptation to climate change impacts.

Keywords: Maize Streak Virus, Random Forest, Phenology, Unmanned aerial Vehicles)

References

Araus, J.L., & Cairns, J.E. (2014). Field high-throughput phenotyping: the new crop breeding frontier. *Trends in plant science, 19*, 52-61

Chemura, A., Mutanga, O., & Dube, T. (2017). Separability of coffee leaf rust infection levels with machine learning methods at Sentinel-2 MSI spectral resolutions. *Precision Agriculture, 18*, 859-881

Mutanga, O., Dube, T., & Galal, O. (2017). Remote sensing of crop health for food security in Africa: Potentials and constraints. *Remote Sensing Applications: Society and Environment, 8*, 231-239

Pal, M. (2005). Random forest classifier for remote sensing classification. *International Journal of Remote Sensing, 26*, 217-222

White, J.W., Andrade-Sanchez, P., Gore, M.A., Bronson, K.F., Coffelt, T.A., Conley, M.M., Feldmann, K.A., French, A.N., Heun, J.T., & Hunsaker, D.J. (2012). Field-based phenomics for plant genetics research. *Field Crops Research, 133*, 101-112