Mapping Weed Infestation Using Biomass

Y Mkhize, S Madonsela, M Cho, A Ramoelo, P Tsele

National Space Conference 2023

National Research Foundation
NRF

CSIR
Touching lives through innovation

MAIZE

uMbila, Mmopo, Mavhele, Poone, Mbona, Melies

- The third major cereal crop grown in the world
- It is the main food staple in South Africa
- South Africa produces around 4 370 000 to 16 800 00 tons in 7 provinces
- South Africa is in the top 10 of maize producing countries in the world
- South Africa is an important exporter of maize in Africa and is relied on to aid in achieving food security in Southern Africa, notably supplying most of Botswana and Namibia's maize demand in 2020
- FOOD SECURITY

CONTENT SLIDE

- Introduction
- Study Area
- Methods and Materials
- Results

Touching lives through innovation

INTRODUCTION

- Weed infestation remains one of the primary obstacles from achieving maximum crop quality, growth, and yield.

- Crop losses due to weed infestation in maize farms have been estimated between 50 and 90% in Africa.

- The South African Maize Guide (2018) estimated the losses to be at least 10% for any South African field.

- These devastating crop losses are a result of the competition between the crop and weed species, where weeds often display efficiency in resource and nutrient consumption

INTRODUCTION

- This occurs in the early stages of maize growth, where the resulting diminished nutrient capacity causes long-lasting adverse impacts on the crop

- Consequently, this necessitates weed detection in the early growth stages of maize to enable timely management intervention

MANUAL WEED DETECTION

- Farmers have reported scouting for weed infestation, insects, and disease problems on a regular basis on their most productive corn fields.

- Scouting requires more time to complete over large farms and is expensive, meanwhile, weed management is a time-specific activity and requires timely detection.

- Spatial and temporal variability of weed infestation and its intensity makes past scouting data obsolete.

- This necessitates alternative methods of weed detection to enhance timely management of weed infestations.

REMOTE SENSING

- Mapping of weed infestation in crop farms has been explored using remote sensing data with varying levels of success depending on the nature of remote sensing data being used, the timing of weed detection and intensity of weed infestation.

- MANY studies were not conducted during the weed control phase, and this is likely because spectral mapping of weeds in the early growth stage of the crop is viewed as practically difficult task (Moran et al., 1997;Shapira et al., 2013).

- López-Granados (2011) argued that

  i) many dicotyledonous crops and broad-leaved weeds display similar reflectance profile in the early growth stage and which would require hyperspectral data to discriminate them

  ii) that the distribution of weeds can be patchy for course resolution data.

MAIZE FARMS

- Maize fields in the early growth are usually characterized by high spatial heterogeneity due to the variations in maize cover and the intensity of weed infestation and maize canopy cover.

- The intensity of weed infestation also varies across the farm due to the occurrence of different species of weed plants.

- All of these create a vegetation cover gradient with varying levels of background contribution to the reflectance signal captured by the sensor.

- Despite this, many successes are recorded in early weed detection using Hyperspectral Remote Sensing.

SENTINEL-2

Sentinel-2 Bands	Spatial Resolution
Coastal aerosol	60
Blue	10
Green	10
Red	10
Vegetation Red Edge	20
Vegetation Red Edge	20
Vegetation Red Edge	20
Near Infra-Red	10
Near Infra-Red Narrow	20
Shortwave Infra-Red	60
Shortwave Infra-Red	60

- Sentinel-2 with enhanced spectral configuration featuring red-edge bands have been shown to improve vegetative inter and intraclass

- Sentinel-2 data has been shown to produce reasonably high accuracy when mapping plants at species level

- Sentinel-2 has 3-5 days temporal resolution, which allows timely detection

REMOTE SENSING

- However, due to the spectral, spatial, and temporal variation in weed occurrence, these models cannot be generalised and require seasonal training data.

- This often proves untimely for immediate implementation of management decisions.

- In general, many of these models use Vegetation Indices which have indicated other factors such as cover, chlorophyll content, and biomass can aid in weed discrimination from crops.

STANDARD PRACTICE

- Maize is planted around the same time
- It is of the same cultivar
- Therefore, similar cover and biomass is expected in plots during the early growth stages of maize
- In this study, we aim to find a biomass threshold for weed free plots and then estimate biomass to identify plots that are above the threshold as the addition of biomass is expected to result from weed infestation

STUDY AREA

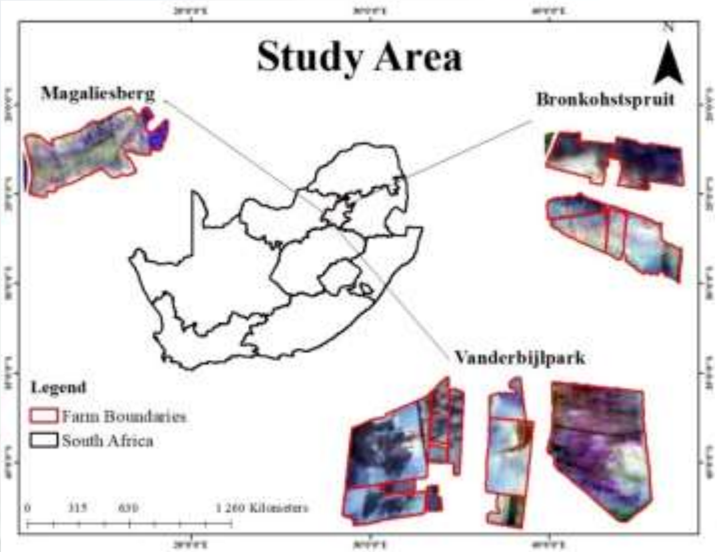


Figure 1: Study areas and their approximate locations within the Gauteng province of South Africa

The study was conducted on 6 maize farms located on the outskirts of the Gauteng Province:
Bronkhorstspruit
Magaliesburg
Vanderbijlpark.

Summer rainfall season which starts in November and ends in March/April and is the main source of water

Common weed plant species :

Richardia *brasiliensis*,

Chenopodium *album*,

Cyperus *esculentus*,

Megathyrsus *maximus*.

LEAF AREA INDEX

- LAI is defined as the amount of leafy area (m^2) in a canopy per unit surface area (m^2)
- LAI significantly influences the plant canopy physiological process, which is closely related to crop productivity.
- Observations on leaf area index (LAI), a measure representative of standing biomass and ground cover
- There are numerous ways of using remotely sensed information to estimate LAI, such as establishing an empirical relationship between the remotely sensed data products such as spectral bands, vegetation indices (VIs) and measured LAI

VEGETATION INDICES

- Vegetation has a strong absorption in the red spectral range and a high reflectance in the NIR, VIs combining these spectral responses may provide an indicator of vegetation “greenness”, and hence a proxy of the LAI

Vegetation Index	Reason For Utilisation
Normalised Difference Vegetation Index (NDVI)	It is the most used and stable VI for estimating the LAI and shows high sensitivity to changes in the crop canopy at early growth stages
Enhanced Vegetation Index (EVI)	Improved from NDVI to reduce the effect of background reflectance and atmospheric errors. It has been reported to detect the maximum LAI earlier than in situ LAI in corn field
Green Leaf Index (GLI)	Sensitive to green vegetation and therefore has a direct relationship with LAI
Red-Edge Normalised Difference Vegetation Index (NDVI-RE)	The red-edge region is strongly related to the physiological status of the plant

REMOTE SENSING DATA

- The study used multiple cloud free Sentinel-2 images acquired within 4 days of the field collection from the Copernicus Open Access Data Hub (https://scihub.copernicus.eu)

- These images collected were Level-2A, which are atmospherically corrected using Sen2Cor

- The 20m red-edge bands were resampled to 10m to match the field dimensions of ground-truthing plots using the nearest neighbor tool in GEE

FIELD DATA COLLECTION

- Collection of maize biophysical variables including maize cover and record the **presence of weeds** in the randomly distributed 10m x 10m sampling plots

- Areas of the farms that had high weed presence or no weed presence were then purposively sampled in the field using the GPS.

- Data was collected in the early growth stages of maize, where an average maize plot has maize with 6-8 leaves, with an average of 35cm in height, and a canopy cover of 10%.

In total LAI in 57 field points were collected.

Touching lives through innovation

DATA ANALYSIS

- Thresholding was performed using histograms of data distribution and validated using the margin of error

- Vegetation Indices were correlated with field measured LAI to determine suitability to use in the regression model

- The study used the Random Forest (RF) from the randomForest package in R 4.2.1 (RColorBrewer and Liaw, 2018) to perform a regression analysis.

- To fulfil RF parameter requirements:

  100 decision trees

  mtry= 8

- The regression consist of the 4 vegetation indices and their relationship to measures LAI.

- The data was partitioned into a 70/30 for training and validation.

ACCURACY

- A linear regression was performed between field data and predicted data to produce R^2
- A Root Mean Squared Error (RMSE) was generated for both validation and test data

Results: Sentinel 2 (20/21/22)

- 57 Points

  Maize: 22
  Weeds: 35

Thresholding revealed an LAI of 1.5

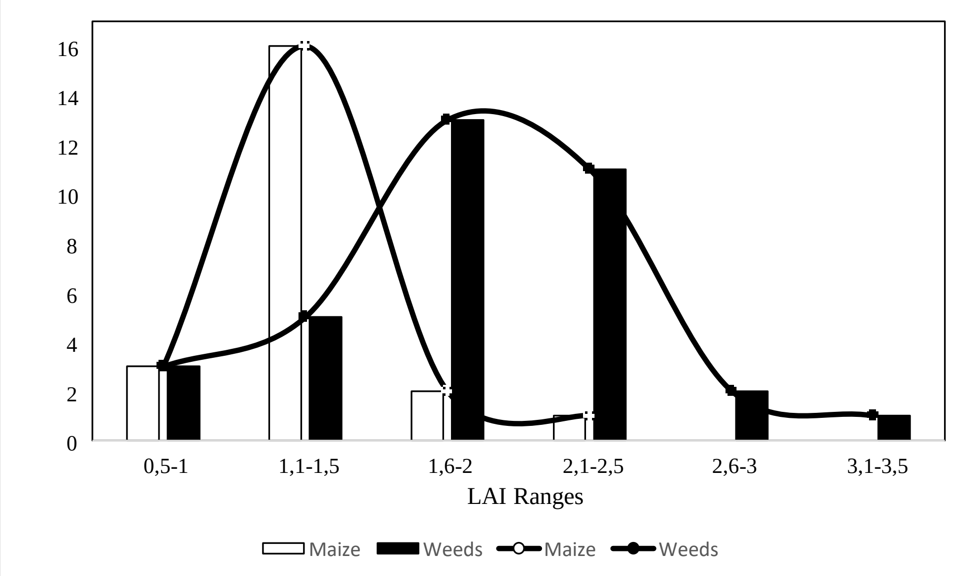
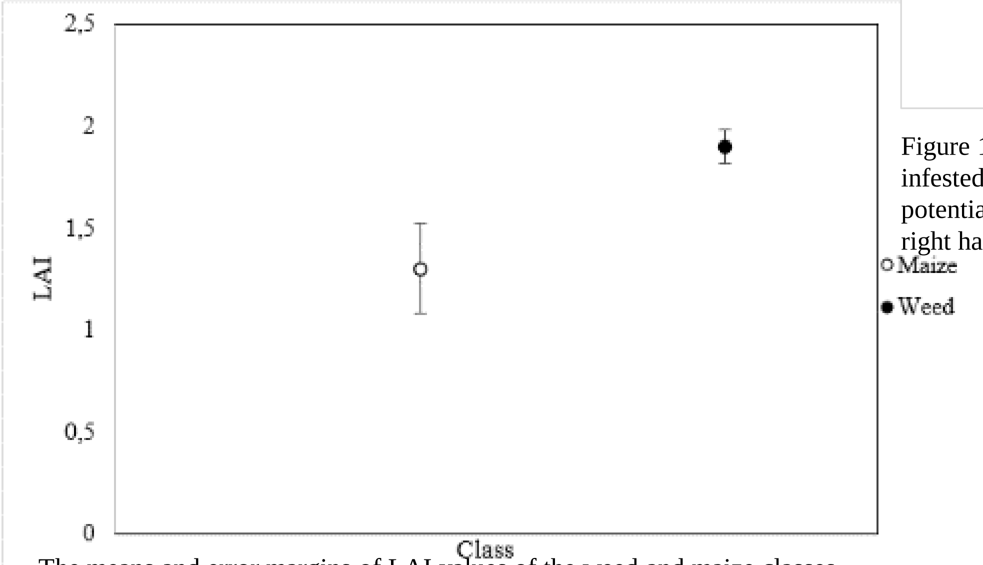


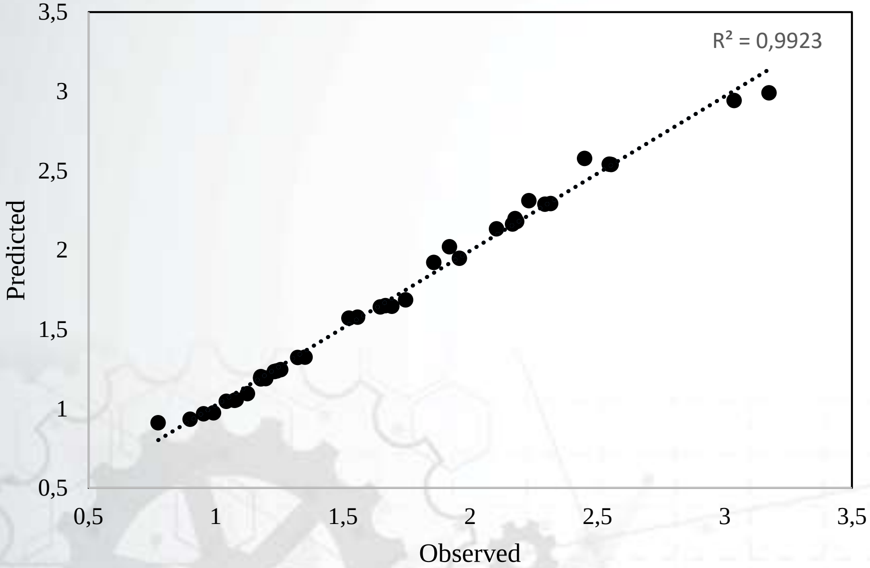
Figure 1:This graph shows the distribution of LAI of recorded data of weed free and weed infested plots. The intersection of the 2 lines reflects the LAI values where there are potentially mixed plots. The LAI values on the left mostly have weed free plots whilst the right has weed infested plots.



The means and error margins of LAI values of the weed and maize classes where both classes respect the 1.6 limit

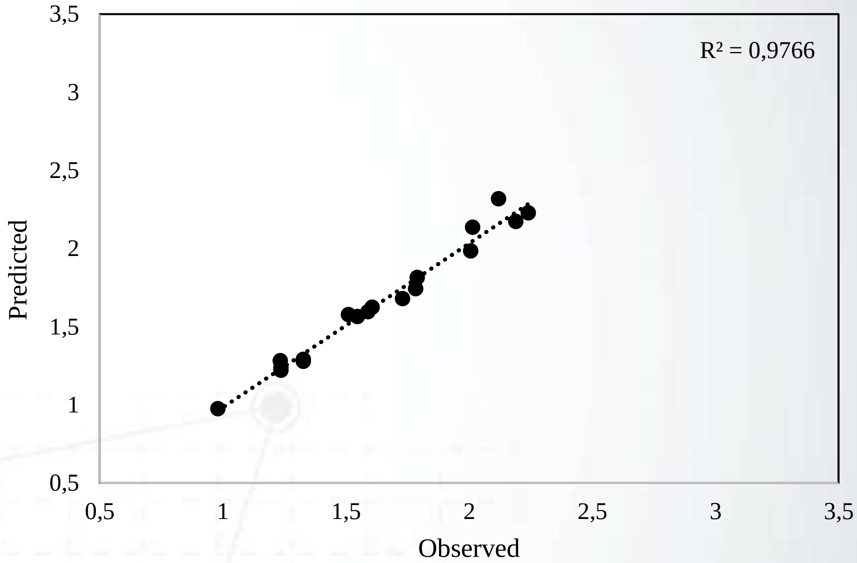
Regression: Vegetation Indices

Training



$R^2 = 0.9923$
RMSE= 0.054409

Test



$R^2 = 0.9766$
RMSE=0.06311

INTERPRETATION

- R^2 indicates the percentage of the variance in the dependent variable that the independent variables explain collectively, which in this case were 0,97 for test data.

- RMSE is a measure of how accurately the model predicts the response, the closer it is to 1 the more accurate the model is.

- The regression model was successful due to its ability to accurately estimate LAI values with slight differences. This further reflect that the model accurately estimate LAI, and therefore can be used in weed detection.

- **NEXT STEP:**
  - Add more data to increase robustness

REFERENCES

- Asner, G.P. 1998. Biophysical and biochemical sources of variability in canopy reflectance, *Remote sensing of Environment*, *64*(3). pp.234-253.
- Cochrane, M.A,, 2000. Using vegetation reflectance variability for species level classification of hyperspectral data, *International journal of remote sensing*. *21*(10). pp.2075-2087.
- Dhau, I., Dube, T. and Mushore, T.D., 2021. Examining the prospects of sentinel-2 multispectral data in detecting and mapping maize streak virus severity in smallholder Ofcolaco farms, South Africa. *Geocarto International*, *36*(16), pp.1873-1883.
- Gao, J., Liao, W., Nuyttens, D., Lootens, P., Vangeyte, J., Pižurica, A., He, Y. and Pieters, J.G., 2018. Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery. *International journal of applied earth observation and geoinformation*, *67*, pp.43-53.
- Lamb, D.W. and Brown, R.B., 2001. Pa—precision agriculture: Remote-sensing and mapping of weeds in crops. *Journal of Agricultural Engineering Research*, *78*(2), pp.117-125.
- Lehoczky, E. and Reisinger, P., 2003. Study on the weed-crop competition for nutrients in maize. *Communications in agricultural and applied biological sciences*, *68*(4; PART A), pp.373-380.
- López-Granados, F., 2011. Weed detection for site-specific weed management: mapping and real-time approaches. *Weed Research*, *51*(1), pp.1-11.
- Moran, M.S., Inoue, Y. and Barnes, E.M., 1997. Opportunities and limitations for image-based remote sensing in precision crop management. *Remote sensing of Environment*, *61*(3), pp.319-346.
- Shapira, U., Herrmann, I., Karnieli, A. and Bonfil, D.J., 2013. Field spectroscopy for weed detection in wheat and chickpea fields. *International journal of remote sensing*, *34*(17), pp.6094-6108.

ACKNOWLEDGEMENTS

- The authors are grateful to the CSIR and National Research Foundation for supporting this study through Parliamentary Grant and Competitive Support for Rated Researcher Grant. The authors also like to thank Mr A. Njoro, Mr W. Sikhosana, Mr V Mahlangu for access to their farms.

- We also would like to thank the University of Pretoria for their contribution in the study

END