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Modelling of Intra-Field Winter Wheat Crop Growth Variability Using in Situ Measurements, UAV Derived Vegetation Indices, Soil Properties, and Machine Learning Algorithms†

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Abstract: Crop growth and yield often vary, not only between farms, but also at the sub-field level. These variations can stem from sub-field heterogeneities of soil and plant biophysical parameters. This means that soil and plant biophysical data can be used to predict intra-field crop growth and yield variability. This study used soil data and vegetation indices (VIs) derived from unmanned aerial vehicle (UAV) imagery as predictor variables and, monthly measurements of crop height (cm) as a response variable to predict crop growth rate in two winter wheat farms in South Africa. These datasets were analyzed using two regression models including Gaussian process regression (GPR) and Ensemble Learning that uses least- squares boosting (LSboost) and bagging (Bag) in MATLAB. Results showed that soil properties, particularly Ca, Mg, K and Clay were more important than VIs in predicting actual crop growth. Furthermore, GPR (R^2 = 0.68 to 0.75, RMSE = 15.85 to 18.38 cm) performed slightly better than LSboost-Bag-ER (R^2 = 0.64 to 0.70 and RMSE = 17.26 to 19.34 cm) for predicting crop growth in both farms. These findings are useful for crop agronomic management.

Keywords: wheat; UAV; vegetation indices; soil properties; gaussian process regression; least-squares boosting and bagging regression

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1. Introduction

Wheat is one of the most widely grown cereal crops around the world [1]. Approximately 36% of the world human population consume wheat products [2]. Due to the inevitable human population growth, there is a rapid increase of cereal production demand and supply, which have to meet global food market needs. Achieving food security and meeting the growing human population demands requires improvements on crop yields. Crop-related factors such as soils and plant biophysical parameters are spatially heterogeneous and their complex interactions greatly affect crop growth rate and yields [3]. This heterogeneity occurs at intra-field level, hence, it is important to investigate and understand the influence of soil properties and plant biophysical parameters on crop development and crop yields.

Soil physical and chemical properties including texture, phosphorus (P), nitrogen (N), potassium (K), sodium (Na), calcium (Ca), magnesium (Mg), and pH influence crop growth. Soil chemical properties, particularly, occur in low concentrations within arid and semi-arid environments, which is detrimental for crop growth [4]. Other factors that impede crop development include droughts, frost, waterlogging, salinity, high temperatures, diseases, weeds, and pests [4].

Vegetation indices (VIs) are good indicators of plant health and they can be used to monitor intra-field crop stress [4]. UAVs provide high-resolution remote sensing images that can be used for intra-field monitoring of crop fields. In addition to UAV-derived high-resolution imagery, machine learning algorithms have been used for estimating biophysical parameters of crops [5]. This study explores kernel-based GPR and non-kernel-based LSboost-Bag-ER machine learning for modelling wheat growth variability from UAV and soil properties data fusion. The aim of this study was to investigate the contribution of soil properties and UAV data to improve modelling accuracy of intra-field crop growth variability for winter wheat. The following objectives help to achieve overall aim of the study (i) investigate and understand the contribution of soil properties and VIs in modelling of crop height growth at heterogeneous winter wheat in dryland environment; (2) assess the prediction accuracy improvement using VIs only scenario, and combined VIs with soil properties scenario for GPR and LSboost-Bag-ER modelling of intra-field wheat crop growth.

2. Materials and Methods

2.1. Study Area

The study was conducted in two winter wheat farms (Figure1, farm A & B) that cover about 30 and 17 hectares, respectively). The farms are in Clarens, which is in Dihlabeng Local Municipality under Thabo Mofutsanyane District Municipality, Free State Province, South Africa. Fertilizer application rate was 100 kg/ha of Cireun fertilizer with the ratio N:55:P:15: K:8, and the wheat cultivar was PAN: 3161. PAN: 3161 is a winter wheat cultivar suitable for dryland production areas of the Free State Province.

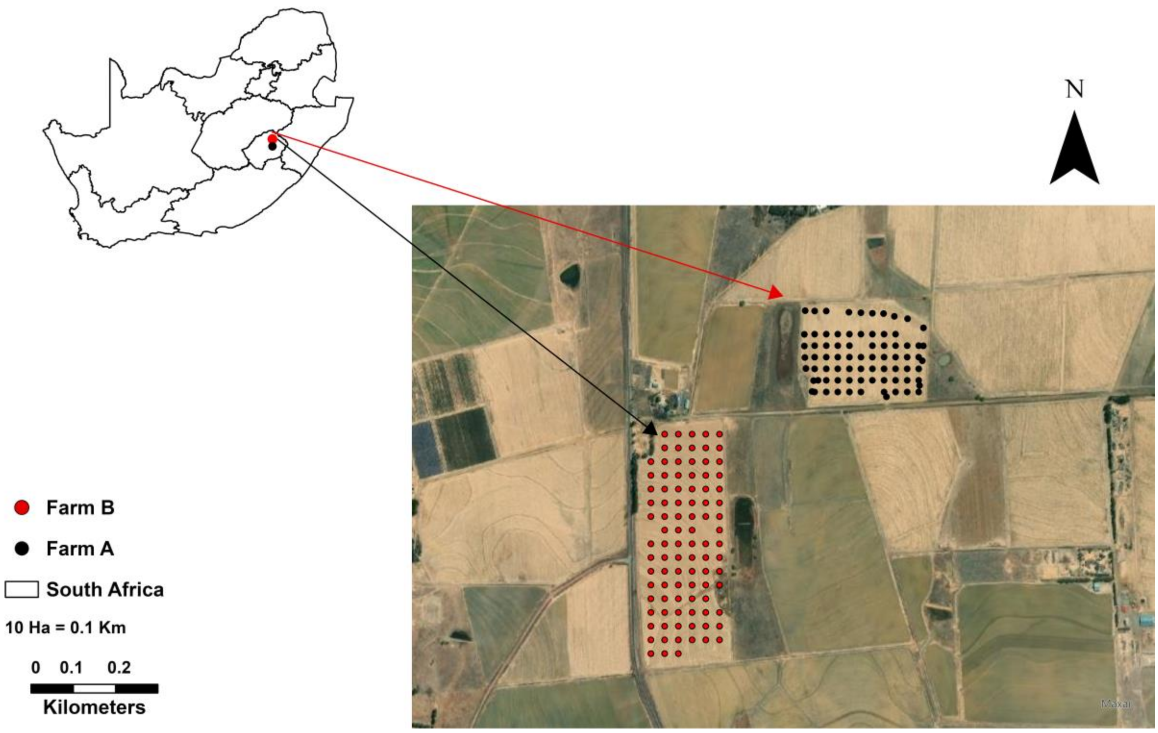

Figure 1. Location of Clarence wheat farms, Free State province, South Africa.

2.2. Methodology

Figure 2 is a summary of the methodology this used to investigate the performances of VIs and soil properties in prediction of crop growth variability. The soil data produced interpolated and continuous distribution maps. Additionally, UAV data generated VIs distribution maps. Both soil and VIs map data were input predictor variables for predicting in-situ crop height growth (response variable). Datasets was divided into 80% training and 20% testing for GRP, and ER models. The training and testing included VIs experiment scenario and integration of VIs and soil physical and chemical properties. Model evaluation accuracy was generated using, mean absolute Error (MAE), root mean square error (RMSE), and coefficient of determination (R^2).

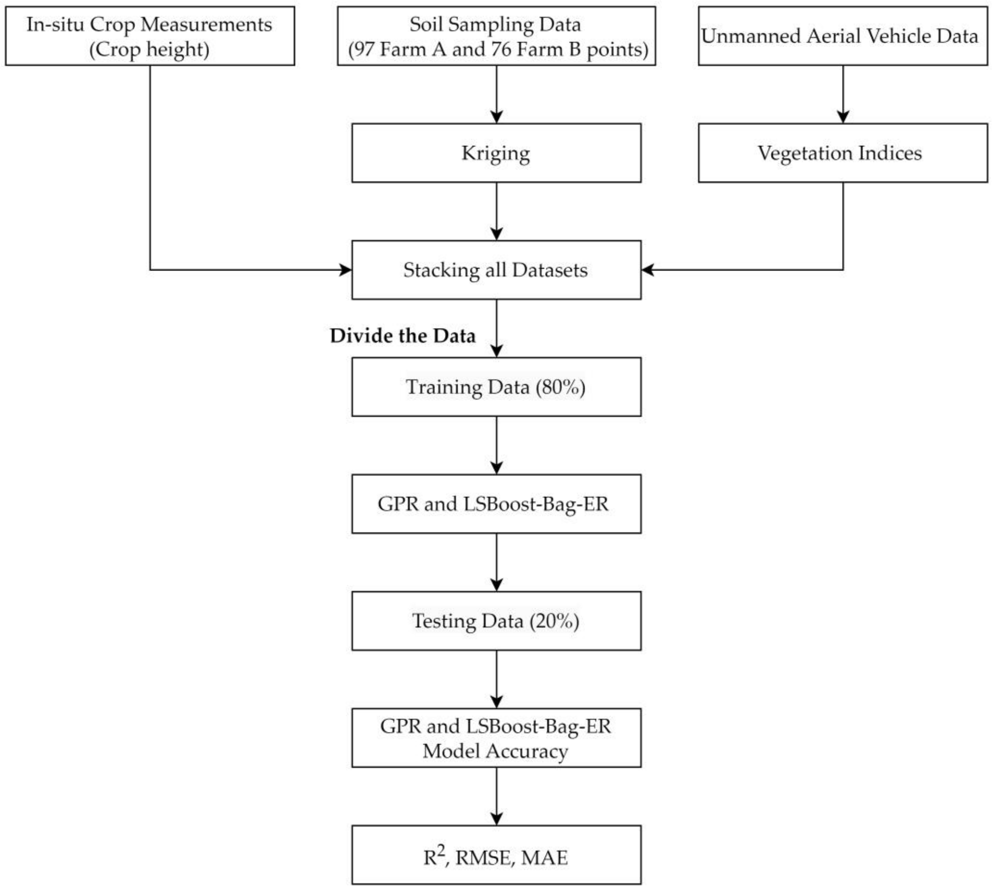

Figure 2. Methodology flowchart for intra-field crop growth modelling used in this study.

2.3. UAV Camera Properties and Vegetation Indices Used in This Study

Table 1 present the spectral band information of MicaSense RedEdge-MX multispectral sensor and Table 2 summarize the VIs generated using UAV imagery bands. However, Figure 3 show multi-rotor DJI-Matrice 600 Pro.

Table 1. Properties of UAV MicaSense RedEdge-MX series sensor.

Bands	Center wavelength (nm)	Band width
Blue	475	20
Green	560	20
Red	668	10
RedEdge	717	10
Near Infrared (NIR)	840	40

Table 2. List of vegetation indices used in this study.

Vegetation indices	Formula	References
Normalized Difference RedEdge Index (RENDI)	$\frac{NIR - Red\ Edge}{NIR + Red\ Edge}$	[3,4]
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - Red}{NIR + Red}$	[3,4]
Normalized Difference Index (NDI)	$\frac{RedEdge - Red}{RedEdge + Red}$	[3,4]
Ratio vegetation index 2 (RVI2)	$\frac{Red}{RedEdge}$	[4]

Figure 3. Multi-rotor DJI-Matrice 600 Pro and Calibration Reflectance Panel (CRP). .

3. Results

3.1. Correlation Matrix

Correlation analyses showed that soil properties, particularly Ca, Mg, K and Clay were more important than VIs in representing actual crop growth for both winter wheat farms (Figure 4 and Figure 5). However, there was a high intra-field variability for all collected soil properties in farm A and farm B. For instance, farm B Mg (r = 0.7), K (r = 0.61), and Clay (r = 0.49) had higher correlation with actual crop height growth than farm A Mg (r = 0.34), k (r = 0.33), and Clay (r = 0.18), respectively.

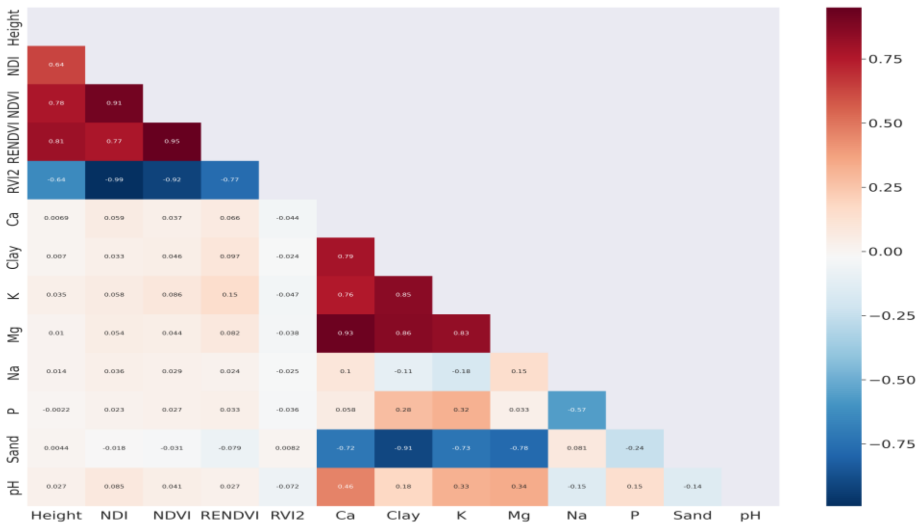

Figure 4. Farm A, pearson correlation matrix of VIs and soil physical and chemical properties.

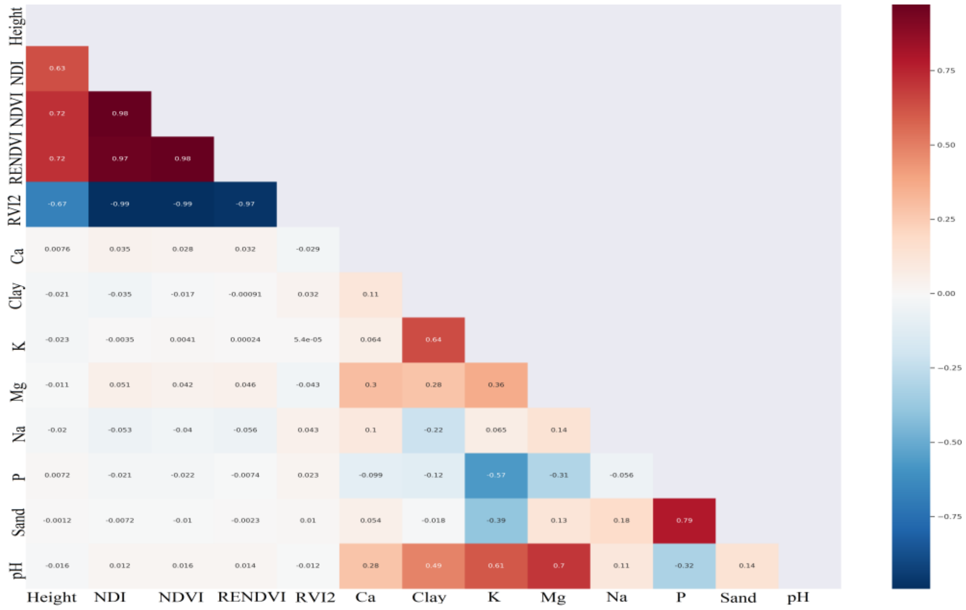

Figure 5. Farm B, Pearson correlation matrix of VIs and soil physical and chemical properties. .

3.2. Model Evaluation

The performance of GPR and LSboost-Bag-ER models accuracy statistics is summarized in Table 3. GPR (R^2 = 0.68 to 0.75, RMSE = 15.85 to 18.38 cm) model performed better than LSboost-Bag-ER (R^2 = 0.64 to 0.70 and RMSE = 17.26 to 19.34 cm) for both farms. Furthermore, GPR was the best performing model with highest accuracy of crop growth prediction when soil properties and UAV derived VIs predictor variables combined. The VIs experiment predictor variables alone generated lowest modelling accuracies for the crop growth.

Table 3. GPR and LSboost-Bag-ER model performance.

Wheat farms	Predictor variables	Model	R^2	MAE	RMSE
Farm A	VIs	GPR	0.72	12.11	16.63
	VIs and Soil properties	GPR	0.75	11.43	15.85
	VIs	LSboost-Bag-ER	0.70	12.51	17.41
	VIs and Soil properties	LSboost-Bag-ER	0.70	12.65	17.26
Farm B	VIs	GPR	0.67	12.38	18.63
	VIs and Soil properties	GPR	0.68	12.77	18.38
	VIs	LSboost-Bag-ER	0.64	12.66	19.35
	VIs and Soil properties	LSboost-Bag-ER	0.64	13.02	19.34

4. Conclusions

This study investigated the performances of in-situ soil properties and monthly time-series UAV data in predicting intra-field crop growth variability in a winter wheat farm. Findings from this study revealed that VIs separately and both soil properties and VIs can be used to predict the actual wheat crop growth. The key findings from this study are associated with the efficiency of data fusion approach to enhance modelling precision and provide the useful information about soil properties influence in prediction of crop height growth. This study will benefit crop agronomic management and increase potential yields.

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Conflicts of Interest: The authors declare no conflict of interest.

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