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Research Paper

Phenology-based winter wheat classification for crop growth monitoring using multi-temporal sentinel-2 satellite data

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ABSTRACT

Wheat is one of the most important staple crops consumed by more than four billion people in the world. However, its production is challenged by the impact of climate change which accounts for a 5.5 % reduction in wheat yield and it is predicted to dwindle further by about 30 % in 2050, due to trends in temperature, precipitation, and carbon dioxide. An effective annual crop estimate is necessary not only to inform governments the status of national food security, but also to determine the benchmark on which agricultural commodities are priced in the market. Thus, annual crop monitoring and yield estimate is paramount to determine the amount of wheat imports required to make up for the shortfalls in the national wheat production in South Africa, which has been a net importer of wheat since 1998. This study aimed at investigating the most distinguishable crop phenology for accurate winter wheat classification during the growing season from August – December 2020 using Sentinel-2 imageries and Random Forest algorithm. The winter wheat crop was more accurately identified during the crop 'heading' stage in October yielding the highest user's (75.56 %) and producer's (92.52 %) accuracies, despite the relatively lower overall accuracy (78.14 %) compared to that of December with overall accuracy of 83.58 % obtained during the maturity stage. This study, therefore, found that the extraction of NDVI values of the winter wheat crop over the period of the growing season using the Sentinel-2 NDVI series method and grouping these values into distinct classes using the K-means unsupervised clustering techniques assist to identify the different crop phenologies based on which the winter wheat crop could be detected and mapped accurately. The phenology-based classification of the winter wheat crop during the heading stage, reduce the ambiguity of spectral confusion created with surrounding grass and maize crops.

1. Introduction

Since its first adoption as a cultivable crop in the Middle East over 10 000 years ago, wheat has been regarded not only as the foundation of a sedentary lifestyle for the early humans but also as a corner stone upon which many civilizations, particularly those in the west thrived on (Curtis and Halford, 2014). It is predominantly a crop of the northern hemisphere, where 90 % of the global production comes from, with China, Russia, and United States of America accounting for 50 % of the world's wheat production (Li et al., 2020). It is one of the three most important staple crops consumed by a third of the world's population (Chang et al., 1994). For most part of the 20th century, wheat production showed a progressive increase, more importantly following the food shortage crisis after the World War II driven by agricultural incentive policies adopted by many countries. The subsidies from the European Union's Common Agricultural Policy encouraged farmers in the United Kingdom (UK) to double average wheat yield from 3.5 t ha^{-1} in 1961 to 7.6 t ha^{-1} in 1984 attracting many barely farmers to switch to wheat

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farming (Curtis and Halford, 2014). Germany was importing over 2 million tons of wheat annually after the war, but became self-sufficient in the 1970s by producing enough for the domestic market (Porsche and Roebbelen, 2008) and it is currently standing at 130 % self-sufficiency produced from a total acreage of 3.1 million ha (Stat, 2015; Laidig et al., 2017). Wheat is also the dominant cereal crop in Poland with cultivation land areas expanding from 20 % in the 1960 to 25 % in the 1980 s to the current 39 % (Oleksiak et al., 2022) accounting for 22 % of the total areas cropped in the country (Iwańska et al., 2020).

The most dominant cereal crop in Southern Africa is maize, but wheat is also grown to supplement the staple maize crop (Shew et al., 2020). The first wheat production in South Africa dates back to 1652 in the Cape of Good Hope and as early as 1684 there was enough wheat production to export to India. The two main commercial wheat species produced in South Africa are the bread wheat (*Triticum aestivum*) and the durum wheat (*Triticum turgidum*), the former accounting for bulk of the wheat production in the country (Nhemachena and Kirsten, 2017). The country is the second largest wheat producer ranking after Ethiopia and wheat is predominantly produced as a dryland crop with irrigation only covering 21 % of the total wheat grown area, which accounts for 41 % of the total wheat production (DAFF, 2014). Wheat production increased from 0.5 t ha^{-1} in 1936 to over 3.5 t ha^{-1} in 2015 leading to 87 % increase in yield and 20 % improvement in the baking quality in the period between 1930 and 1990 (Purchase and Van Lill, 1995). It is mainly produced in the Western Cape, Free State, Northern Cape, North West and Mpumalanga provinces (Department of Agriculture, 2010) with over 42 % of the total 1.5 million ton wheat produced in 2019 com ing from the Western Cape Province (https://www.statista.com/statistics/1135888/wheat-production-in-south-africa-by-province/). Unfortunately, though, South Africa remains a net importer of wheat since 1998 after the wheat growing area declined by 46 % following the changes in policy leading to the deregulation of the wheat market and dissolution of the existing fixed pricing system by the wheat marketing board (Shew et al., 2020). The low profitability of wheat production and other extreme climatic conditions (e.g., drought and frost) made farmers lose interest in growing wheat and shift to more profitable crops such as maize and soybean (Sosibo et al., 2017). For instance, the drought incidence of 2015/2016, which particularly hit the Western Cape Province (where more than 90 % of wheat grows in dryland condition), led to South African wheat exports to the Southern African Development Community (SADC) countries drop by 76 % (SADC, 2016). Although a net importer, South Africa does import wheat of lower quality to mix with high quality produced locally and export mainly to other member countries of the Southern African Development Community (SADC) (Shew et al., 2020).

The global population is projected to grow by 35 % and reach 9.3 billion by 2050 (U.S. Census Bureau, 2011), which will require an estimated 70 % increase in food production mainly in wheat, maize, and rice (that collectively occupy 58 % of the annual crop area and account for 50 % of the calories required) to cater for the future food demands (FAO, 2009; Stewart and Roberts, 2012). Wheat production has to increase by 60 % to ensure the global food security of the projected of world population growth (Jaiswal et al., 2017). Many of such production increases are expected to come from developing countries, where agricultural lands must double, and the low production level improve through intensive farming. Most of the production in these countries, is however dependent on dryland conditions and due to climate change effects, which causes a variable and unpredictable weather conditions and increased drought frequencies, crop production might suffer a setback to meet the growing global food demand. Irrigation farming could be the focus of future crop production for a substantial contribution in the global food security, but water resources are limited and requires effective management, which will depend on accurate and timely crop-type knowledge for robust water budget and irrigation plans. This is particularly important in arid and semi-arid regions of the world, where most of the land expansion required to increase future food will come from.

Crop yield forecast during the growing season before harvest is paramount not only to facilitate the decision making of whether or not to import seasonal shortfalls of staple crop production to ensure food security, but also seasonal crop estimates produced nationally are used as a benchmark on which agricultural commodities are priced in the market and it has a direct bearing on decisions taken by government, farmers, and the business community by large. The two components required for crop production forecast are the crop acreage and the expected acres to harvest (Vogel and Bange, 2004); where crop-type mapping is the most important aspect of crop management and yield forecast to characterize the dynamic and unpredictable changes of the agricultural land cover patterns (Zhong et al., 2011). For many years crop estimate depended on complete censuses, sample survey systems from farmers' reports, observed data from large point samples, conventional area frame systems, and data obtained from administrative offices (Craig and Atkinson, 2013). Either as a separate estimation or a partial survey for ground-truthing of the recent remote sensing–based crop estimate methodology, crop area survey remains widely in practice across the world (Craig and Atkinson, 2013). Although such traditional area survey methods could be accurate, they are expensive, labour and time demanding, and do not produce accurate crop spatial distribution (Pan et al., 2021). The advent of high spatial and spectral resolution remote sensing technology has, however, allowed the crop estimation data survey to evolve and satellite imageries are currently used for agricultural land classification and estimation of acreages to be planted or harvested. It has become a popular tool of choice for crop yield forecast. Thus, although complete census is still in practice in many countries, remote sensing and sample ground survey for training has synergistically revolutionized the crop-type mapping methodology.

The different crop biological events from planting to harvest over the growing season, referred as crop phenology, depends on climatic, edaphic, and agronomic practices, and varies with time and location (Gao and Zhang, 2021). Timely mapping of such changes in crop developmental stages are significant for crop growth management, such as determining the irrigation and fertilizer requirement regimes, which could be scheduled on the phenological stage, and crop yield forecast (Gao and Zhang, 2021). Different vegetative indices (VI) are used to determine crop phenology using the changes in the vegetation status following the different developmental stages such as green-up, heading and senescence. The progressive advancement in the temporal and spatial resolutions of satellite observation on the earth surface has enabled the use of a near-real time approach to monitor crop growth on pixel basis.

While the utility of remote sensing to classify and characterize different crop-types has been previously studied, this study particularly focused on crop-phenology based classification using temporal and spatial remote sensing satellite data. It aimed at investigating effective methods of extracting and clustering NDVI values obtained during the crop growth period to match the known crop phenologies of winter wheat crop for an accurate classification of winter wheat based on the crop phenology.

2. Materials and methods

2.1. Study area

The study was conducted around the town of Reitz in the Thabo Mafutsanyane District, the Free State Province of South Africa, the second biggest wheat producer in the country after the Western Cape Province (Fig. 1). Reitze is located (27°48′6.23″S and 28°25′31.54″E) in th north-eastern part of the province and experiences a humid-subtropical climate with average annual precipitation in the region ranging from 300 – 900 mm (Moeletsi, 2010). It is predominatly planted with winter wheat from late July to early August and yellow maize from Ootober depending on the onset of rainfall.

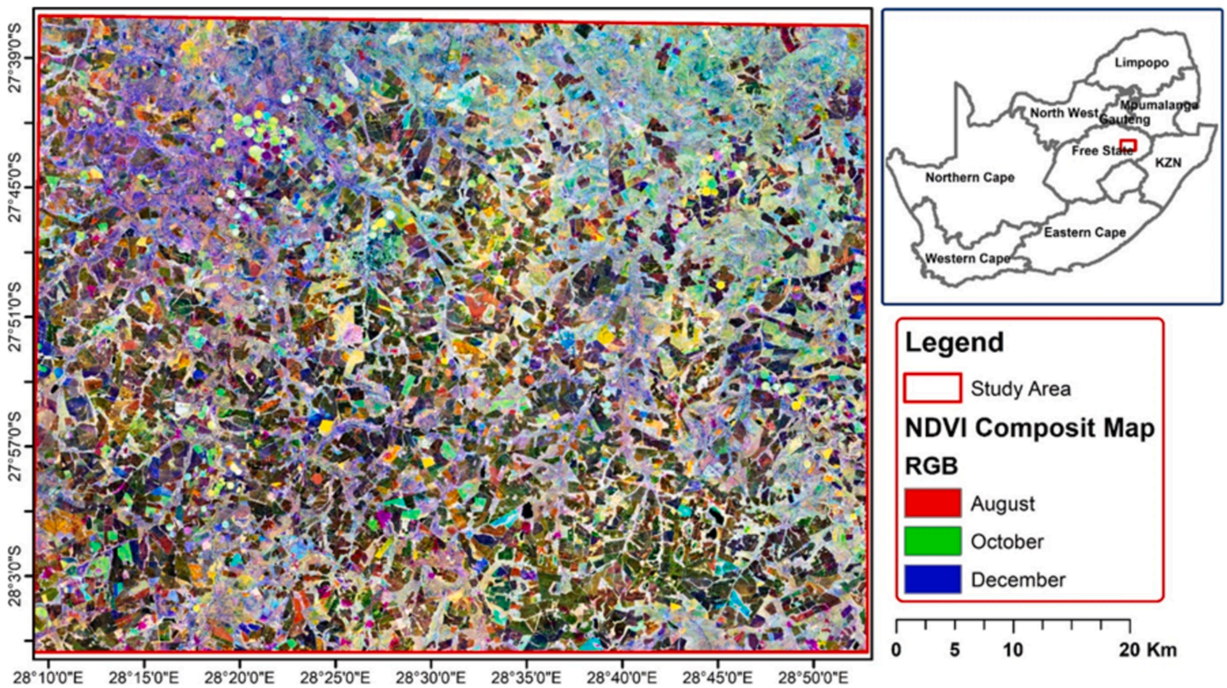

Fig. 1. Sentinel-2 Normalized Difference Vegetation Index (NDVI) composite map of the study areas in Reitz, Free State Province, South Africa.

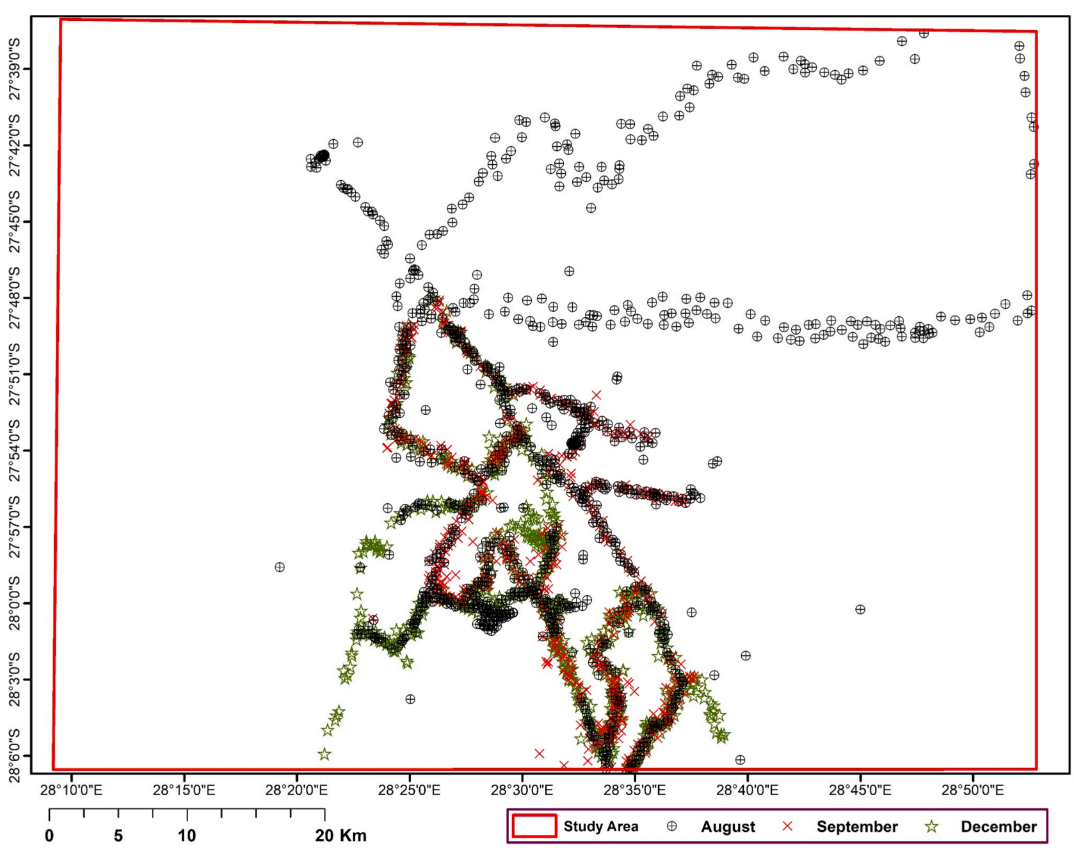

Fig. 2. Ground-truthing Global Positioning System (GPS) points collected during the growing season of winter wheat in August, October and December.

2.2. Data acquisition

A handheld Global Positioning System (GPS) receiver (Garmin eTrex 20 X) was used to collect 2 017 coordinates from the months of August (521), October (686) and December (803) during the growing season of winter wheat crop in 2020 (Fig. 2). Among some of the land use land cover (LULC) classes were water, natural vegetation, furrow, maize, grass, beans, built up and winter wheat including their phenological stages.

Fig. 3. The different phenological stages of winter wheat during the growing season from August to December 2020 in Reitz, Free State Province, South Africa.

2.3. Image classification using Random Forest

The multispectral Sentinel-2 satellite imageries with cloud cover of less <5 % were selected for the phenology-based classification using the Random Forest (RF) algorithm and the classification accuracy was computed in a confusion matrix table. The total (2 017) ground truthing GPS dataset was split into two as a training subset data accounting for two-third (70 %) of the total data and the remaining third (30 %) of the data as a validation dataset for the Random Forest classification algorithm from which the accuracy assessment matrix including overall,

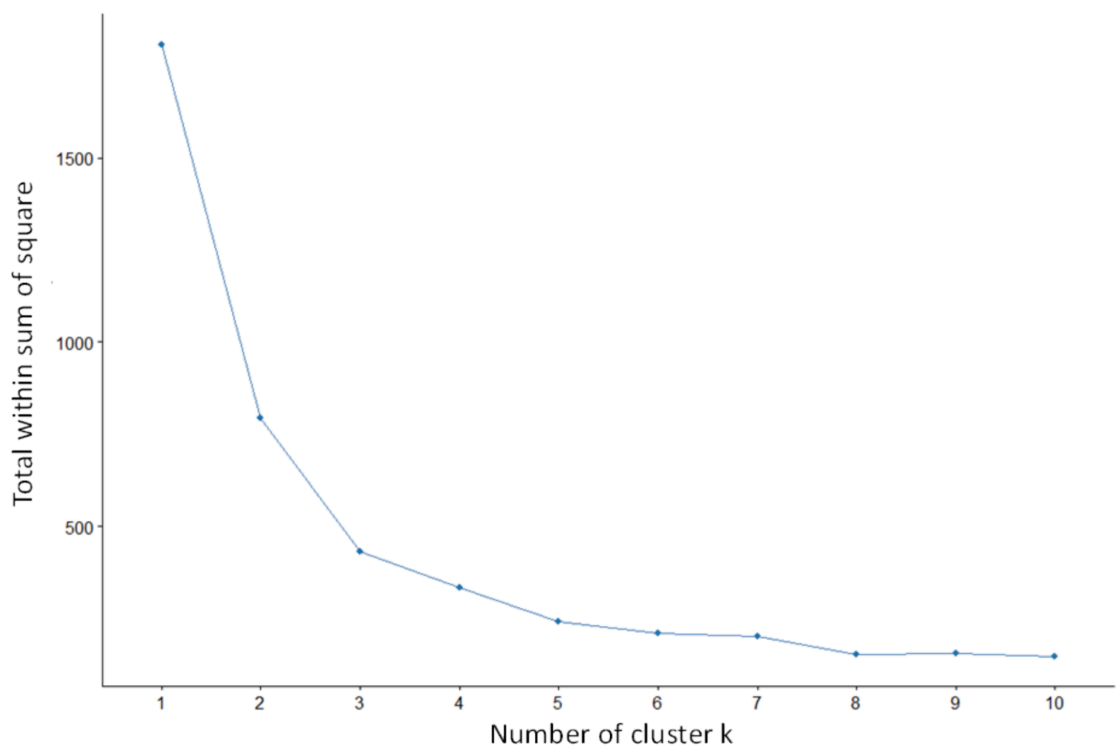

Fig. 4. Elbow method used to determine the optimum number of clusters required to group the datasets into based on their similarity.

producer's and user's accuracies, and the kappa coefficient were computed to determine the classification accuracy of the Sentinel-2 imageries. The winter wheat dataset obtained from 130 farms were clustered into groups from the NDVI time series values averaged from 14 days of the winter wheat growing season spanning from August to December to determine the optimum number of k-means cluster using Iso Cluster Unsupervised Classification algorithm on R software.

2.4. Plant phenology

The most common phrenological stages of winter wheat (Fig. 3.) includes Tillering (from germination stage with a single shoot to 2–5 shoots), Jointing (when first nodes appears above the soil surface), Booting (when the flag sheath swollen enclosing the awns), Heading (when the first anther appears) and Flowering (when anthers covers the entire head), Maturity (when developed kernel contains 40 % of moisture and can be split by fingernail) and Ripening (when kernel moisture content is about 13 % and turns golden in colour and becomes harder to split with fingernail) (Knott, 2016).

3. Results

The K-means, a common algorithm for unsupervised classification of large dataset was used to determine the optimum number of clusters required to group the entire winter wheat dataset according to their similarities. The point in the cluster curve at which the decline the

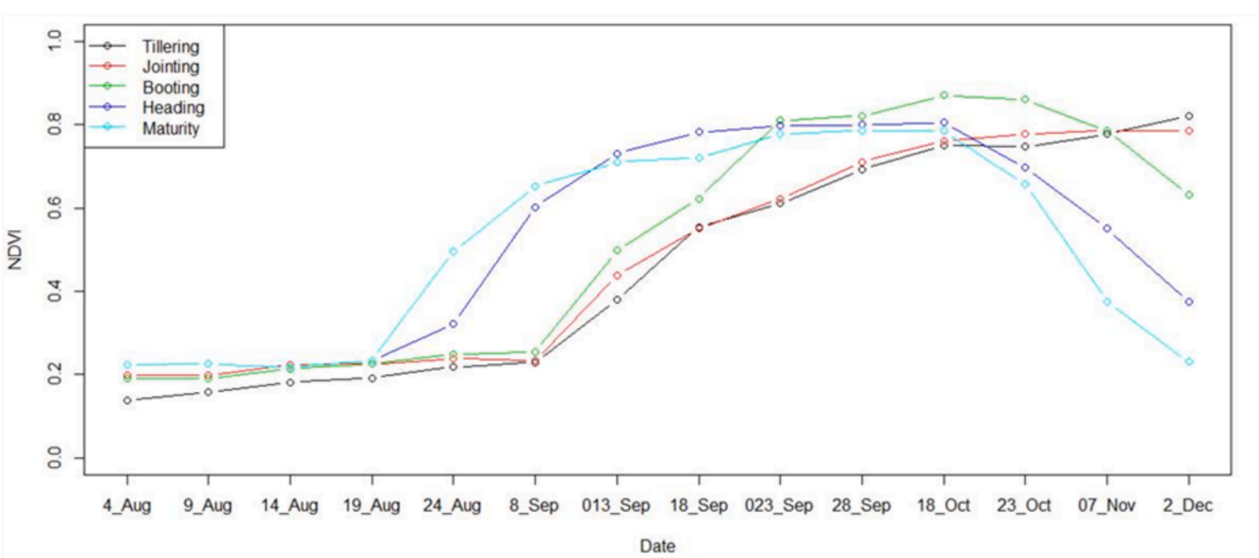

Fig. 5. NDVI of winter wheat during the growing season from Aug – December 2020 in Reitz, Free State Province.

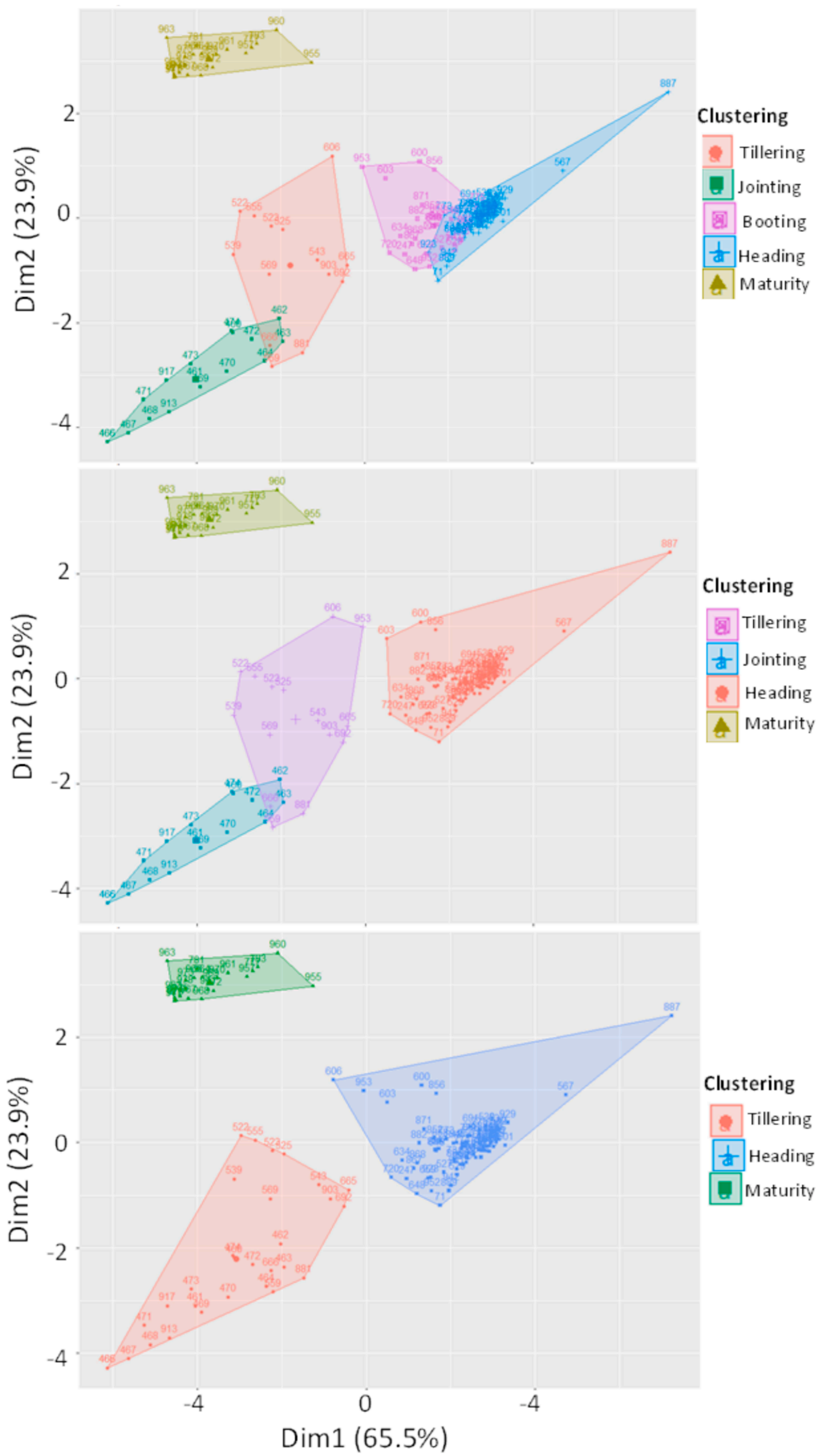

Fig. 6. Unsupervised classification of winter wheat dataset using K-mean clustering algorithm.

distortion was the lowest also referred as the 'elbow' indicates the optimum k value (number of clusters) into which the data set will be grouped. The results showed the optimum or the smallest number of clusters with low sum of squared errors (SSE) was at k 3, after which the SSE diminished for every increasing k cluster (Fig. 4).

A total of 130 GPS points were collected from each winter wheat farm in the study area in early October 2020. The boundary of each farm containing a GPS point was then drawn into a polygon and as many as

Table 1
Accuracy assessment of unsupervised classification of winter wheat dataset using k-mean clustering algorithm into which crop phenological stages were grouped.

a. The classification accuracy of dataset grouped into five clusters using the K-means clustering

Growth stages	Tillering	Jointing	Booting	Heading	Maturity	Total	UA
Tillering	582	291	73	72	0	1018	57.17%
Jointing	710	1065	118	118	0	2011	52.96%
Booting	31	64	958	542	0	1595	60.06%
Heading	0	225	561	1685	112	2583	65.23%
Maturity	0	0	41	81	937	1059	88.48%
Total	1323	1645	1751	2498	1049	8266	
PA	43.99%	64.74%	54.71%	67.45%	89.32%		**OA = 63.23%**

b. The classification accuracy of dataset grouped into four clusters using the K-means clustering

Growth stages	Tillering	Jointing	Heading	Maturity	Total	UA
Tillering	582	363	73	0	1018	57.11%
Jointing	710	946	355	0	2011	47.04%
Heading	57	114	3835	172	4178	91.79%
Maturity	0	41	163	855	1059	80.74%
Total	1349	1465	4426	1027	8267	
PA	43.14%	64.57%	86.65%	83.25%		**OA = 75.21%**

c. The classification accuracy of dataset grouped into three clusters using the K-means clustering

Growth stages	Tillering	Heading	Maturity	Total	UA
Tillering	2834	195	0	3029	93.56%
Heading	114	3778	286	4178	90.43%
Maturity	41	203	815	1059	76.96%
Total	2989	4176	1101	8266	
PA	94.81%	90.47%	74.02%		**OA = 89.33%**

1018, 1595, 2011, 2583 and 1595 points were generated for each of the phenological stages namely tillering, Jointing, Booting, Heading and Maturity, respectively. Sentinel-2 NDVI times series values over the period of 14 days spanning from 1 August to 31 December 2020 were extracted using Google Earth Engine software and classified using K-means clustering technique across the study area. There were five distinct groups with varying NDVI values over the growth period (Fig. 5).

Although the optimum number of clusters into which the winter wheat dataset will be grouped is calculated at K 3, unsupervised clustering was also calculated for K 5 and K 4. The results showed crop phenological stage of 'Maturity' was consistently separable for all clustering groups of K-3, K-4 and K-5 (Fig. 6). When the dataset was clustered into five groups, there was an overlap between the winter wheat crop stages 'Booting and Heading, as well as between Tillering and Jointing. The same was true in the latter when the clustering was reduced to four groups. However, clustering them into a group of 3, showed no overlap between Tillering, Heading and Maturity.

The overall accuracy (OA) of the unsupervised classification using the k-mean clustering algorithm was the highest at the optimum cluster number of K-3 with 89.33 % compared to 63.23 % and 75.21 % when the dataset was grouped into clusters of K-5 and K-4, respectively (Table 1). The confusion was more prominent between the Tillering and Jointing and between Booting and Heading crop stages. The user's accuracies (UA) were the lowest in the first two paired stages with 57.17 % and 52.96 %, respectively.

The crop phenology-based classification of the winter wheat using Sentinel-2 satellite imageries and the Random Forest (RF) algorithm during the months of August, October and December 2020 growing season (Fig. 7) produced overall accuracies of 75.16 %, 78.14 % and 83.58 %, respectively (Table 2) increasing with the age of the crop from emergence in August to maturity and ripening in December. In August, the two dominant land use types were extensive furrowed farmlands and early stages of wheat crop tillering, and no other crop stages were identified. The furrow class showed a spectral confusion with grass and wheat emergence. The same was true with the wheat that overlapped largely with furrow followed by grass (Table 2) as a result, the two classes received the lowest user's accuracies of 61.17 % and 62.86 %, respectively. The overall accuracy (78.14 %) of the classification in October showed a slight improvement compared to the first stages of wheat in August. The spectral mix-up, however, remained between the same classes of wheat and furrow, although relatively lower than in the previous month. The wheat tillering (WT) and wheat heading (WH) were the only two phenological stages identified in the study areas recording the highest users' (73.60 % and 75.56 %) and producers' (89.51 % and 92.52 %) accuracies. In December, the last month of the active growing season of the winter wheat crop in the study area (in Reitz) the wheat maturity (WM) was the only phenological stage identified yielding the lowest user's accuracy (67.24 %) and producer's accuracy (70.91 %), despite the highest overall accuracy (83.58 %) recorded.

4. Discussion

Cultivation of winter wheat in Free State Province (Reitz) starts from mid July to the first week of August and harvested in late December. The crops start germinating in winter during the dry season on the existing soil moisture from the previous rainfall season in summer and reach the heading and flowering stages from October with the onset of the summer rainfall and maturity in December. Planting dates of the winter wheat varies from 1 to 3 weeks amongst farmers and therefore, the crop phonological stages of the study areas vary accordingly. The winter wheat crop was mapped using the multispectral Sentinel-2 NDVI time series over a 14-day period stretching from August – December and the wheat dataset was clustered into 3–5 groups using the K-mean unsupervised clustering technique. The different crop phenological stages were matched to each cluster from field observation records. A spectral confusion was observed between the tillering and jointing stages as well as the booting and heading stages when the wheat data set was clustered to five groups (Fig. 6). This either could be due to the different planting dates of the wheat crop across the study areas resulting in an onset of a crop phenological stage in one farm or developing into the next stage in another. The NDVI time series clustering results showed the different grouping of the study area based on the wheat crop phenological stages with varying dates of reaching each crop stages (Fig. 5). The study areas, was however, distinctly clustered when the dataset was classified into

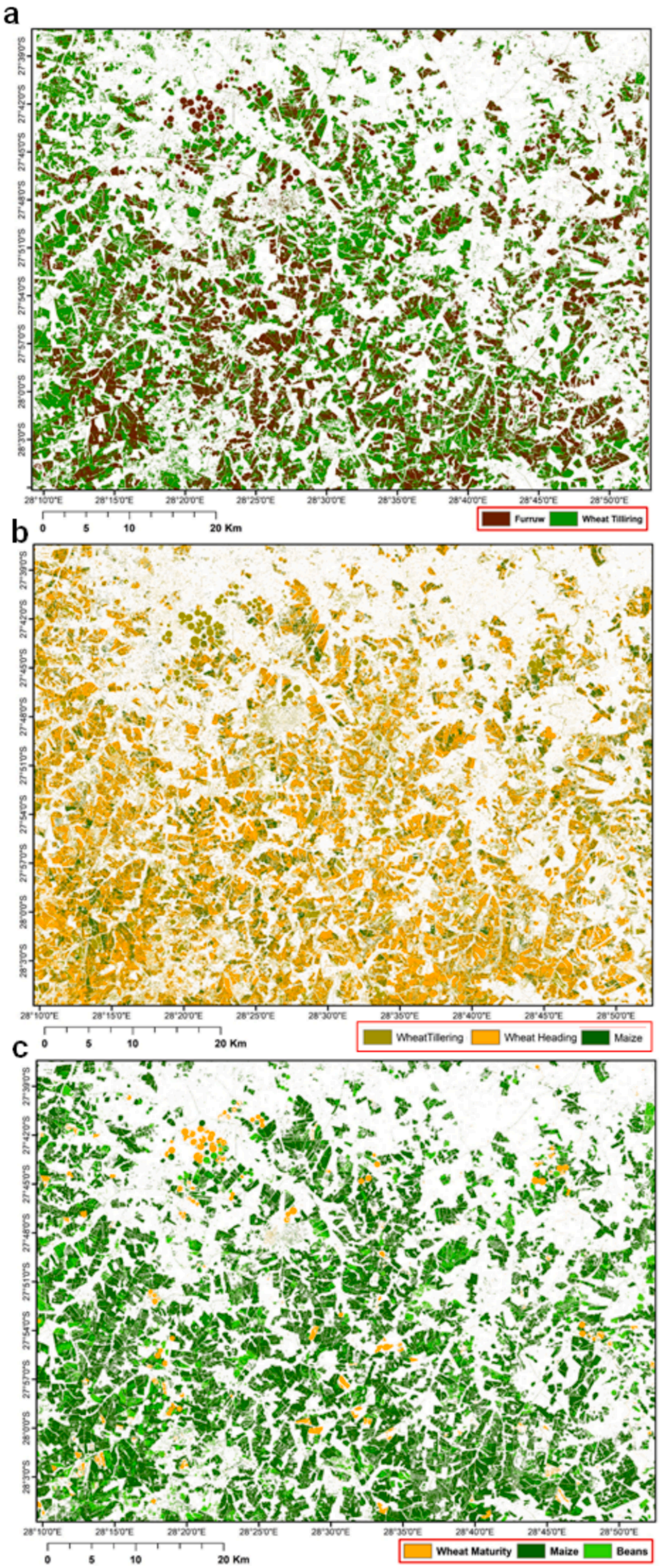

Fig. 7. Classification map of winter wheat using Sentinel-2 satellite data with Random Forest algorithm for (a) August, (b) October and (c) December months of the crop-growing period in Reitz, Free State Province, South Africa.

Table 2
Accuracy assessment of winter wheat classification using Sentinel-2 satellite data with Random Forest for the growing season from Aug – Dec 2020. NB: UA denotes user's accuracy, PA-producer's accuracy, OA-overall accuracy NV-natural vegetation, WT-wheat tillering and WM-wheat maturity.

a. Accuracy assessment for winter wheat classification map in August 2020

Class	Built up	Furrow	Grass	N. veg	Water	Wheat	Total	UA
Built up	25	6	0	0	4	0	35	71.43%
Furrow	1	63	28	0	1	10	103	61.17%
Grass	1	23	187	4	3	4	222	84.23%
N.V	2	5	3	42	1	3	56	75.00%
Water	1	0	0	0	58	1	60	96.67%
Wheat	2	26	13	7	4	88	140	62.86%
Total	32	123	231	53	72	106	616	
PA	**78.13%**	**51.22%**	**80.95%**	**79.25%**	**80.56%**	**83.02%**		**OA = 75.16%**

b. Accuracy assessment for winter wheat classification map in October 2020

Class	Built up	Furrow	Grass	Maize	NV	Water	WT	WH	Total	UA
Built up	30	2	3	0	1	6	0	0	42	71.43%
Furrow	1	79	3	38	0	3	4	0	128	61.72%
Grass	1	3	184	20	6	2	3	4	223	82.51%
Maize	0	37	7	189	0	2	5	0	240	78.75%
NV	6	1	12	4	189	9	1	1	223	84.75%
Water	1	0	0	0	0	60	0	1	62	96.77%
WT	0	11	15	12	2	7	145	5	197	73.60%
WH	0	0	15	4	14	7	4	136	180	75.56%
Total	39	133	239	267	212	96	162	147	1295	
PA	**76.92%**	**59.40%**	**76.99%**	**70.79%**	**89.15%**	**62.50%**	**89.51%**	**92.52%**		**OA = 78.14%**

c. Accuracy assessment for winter wheat classification map in December 2020

Class	Beans	Built up	Furrow	Grass	Maize	N. veg	Water	WM	Total	UA
Beans	27	0	3	3	0	0	1	0	34	79.41%
Built up	0	20	3	5	0	0	0	0	28	71.43%
Furrow	5	1	67	3	2	0	0	16	94	71.28%
Grass	1	0	11	210	13	0	0	9	244	86.07%
Maize	0	0	1	41	210	2	0	3	257	81.71%
NV	1	0	0	0	16	109	0	3	129	84.50%
Water	0	5	0	0	0	0	58	1	64	90.63%
WM	0	2	7	3	23	1	2	78	116	67.24%
Total	34	28	92	265	264	112	61	110	932	
PA	**79.41%**	**71.43%**	**72.83%**	**79.25%**	**79.55%**	**97.32%**	**95.08%**	**70.91%**		**OA = 83.58%**

three groups as tillering, heading and maturity producing the highest overall accuracy of 89.33 %. The winter wheat classification based on phenological stages over the period of August, October and December resulted in overall accuracy of 75.16 %, 78.14 % and 83.58 %, respectively. The highest accuracy result reported during the crop maturity stage in December was higher compared to the overall accuracy of 72.22 % reported in another similar study of phenology-based classification of winter wheat using Sentinel-2 (Nkuna, 2021). The finding of this study was also comparable to the overall accuracy of 84 % reported for winter wheat phenology-based mapping using sentinel-1 (Song and Wang, 2019).

Maize cultivation in the predominantly wheat grown area of Reitz is gradually increasing as wheat production and profitability dwindles due to climatic change effects such as drought and frost during the winter season. It is planted with the onset of the rainy season in fallowed lands or after the harvest of the wheat crop in December. Depending on the planting date, maize spectral signature was found to overlap with the winter wheat crop at tillering stages (Table 2). Thus, although the general classification accuracy in December was the highest during the wheat maturity stage, the users' (67.24 %) and producer's (70.91 %) accuracies were the lowest. 23 maize crops (8.7 %) were misclassified as wheat in December. This is because maize crops planted earlier were past the emergence and seedling stages leading to spectral confusion with the winter wheat. Such interferences from maize were minimal particularly during the heading stage of winter wheat in October with only 1.5 % of maize crops misclassified as wheat. Thus, the winter wheat crop was more clearly identified during the growth stage of 'heading' in October yielding user's and producer's accuracies of 75.56 % and 92.52 %, respectively, despite the relatively lower overall accuracy reported in this month than in December. This conforms with the findings shown by (Tao et al., 2017) who, using time-series MODIS data, also found a maximum enhanced vegetation index (EVI) during the heading stage of the wheat crop in the northern region of China Plain with an accuracy of 92 %. The higher accuracy level compared to the finding in this study was, however, due to the early planting period of wheat when most other crops are either harvested or just sown to make any annual spectral confusion or crop interference. While such time series MODIS imageries could give a substantially high accuracy level in crop classification and was widely used to map crops based on their phenological stages [23;29] under particularly less heterogeneous environments, its coarse resolution is not suitable for small wheat farms.

With the increasing drought frequencies and unpredictable rainfall patterns, it is increasingly becoming inevitable that future food security would gradually depend on partially or fully irrigated lands to produce wheat and other staple crops. Mapping crop-types classification based on crop phenology not only is an important component of crop yield forecast to ensure food security, but also a tool to support farm management and monitoring with scheduled irrigation and fertilizer application during the critical crop developmental stages. Sentinel-2 satellite imagery and the NDVI time series data can be used to effectively classify crops based on crop phenology.

5. Conclusions

The winter wheat crop was mapped using the multispectral Seninel-2 NDVI series that was used to extract the NDVI values over 14-days spanning the three months of August, October, and December during the crop growing period. Using the K-mean unsupervised clustering technique, the NDVI values were then successfully grouped into three distinct classes, which matched the tillering, heading and maturity crop phenologies based on field observation during the growing period. The classification of the Sentinel-2 imagery using the Random Forest algorithm based on these phenological stages produced the highest overall accuracy of 83.58 % in the month of December followed by October with 78.14 % accuracy. Nevertheless, the highest user's and producer's accuracy for the winter wheat were recorded in the month of October during the 'Heading' stage, suggesting that the best time to map winter wheat crop accurately during the growing season is the heading stage. These findings, therefore, implies that despite the different planting date of the winter wheat crop in the region, the extraction of the NDVI values using the Seninel-2 NDVI series techniques, and the K-means unsupervised clustering of the NDVI values, could be matched to the different crop phenologies observed in the field assisting the accurate classification of the winter wheat using this phenologies.

6. Statements and declarations

This synthesis paper is our own original work and has never been published before, nor does any part of it appear in any other publication unless it is fully acknowledged. The manuscript is not being considered for publication elsewhere and thus the authors have agreed to submit this paper for the first time to the 'The Egyptian Journal of Remote Sensing and Space Sciences'. The review article falls well within the scope of the Journal and no ethical permit was required to prepare the work and all collaborations and financial support has been acknowledged.

CRediT authorship contribution statement

Solomon W. Newete: . **Khaled Abutaleb:** Writing – review & editing, Validation, Software, Investigation, Formal analysis, Data curation, Conceptualization. **George J Chirima:** Writing – review & editing, Project administration, Data curation. **Katarzyna Dabrowska-Zielinska:** Writing – review & editing, Methodology, Conceptualization. **Radoslaw Gurdak:** Writing – review & editing.

Declaration of competing interest

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