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Phenology-Based Winter Wheat Classification for Crop Growth Monitoring Using Multi-Temporal Sentinel-2 Satellite Data

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Abstract: The rising global population amidst the growing concerns of climate change will have a dire consequence on global food security and socio-economic activities. Wheat is one of the most important staple foods consumed by more than four billion people in the world, but climate change impacts account for a decline of 5.5% in wheat yield and predictions indicate that the production could further dwindle by nearly 30% in 2050, due to trends in temperature, precipitation, and carbon dioxide. An effective annual crop estimate is necessary not only to inform government the status of national food security, but also is used 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. A joint project between South Africa and Poland investigated satellite based-crop growth monitoring using Sentinel 2 and determined the most distinguishable crop phenology for an accurate winter wheat classification during the growing season from August – December with Random Forest (RF) 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 OA of 83.58% obtained during the maturity stage. This study, therefore, confirms the suitability of sentinel 2 for an effective phenology-based winter wheat crop classification during the heading stage, reducing the ambiguity of spectral confusion created with surrounding grass and maize crops.

Keywords: Phenology; Tillering; Random Forest; Crop type; Clustering; Unsupervised classification

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 [1]. 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 [2]. It is one of the three most important staple crops consumed by a third of the world population [3]. For most part of the 20th century, wheat production showed a progressive increase, more

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importantly following the food shortage crisis after 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 which also attracted many barely farmers to switch to wheat farming [1]. 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 [4] currently standing at 130% self-sufficiency produced from a total acreage of 3.1 million ha [5,6]. Wheat is also the dominant cereal crop in Poland with cultivation land areas expanding from 20% in the 1960 to 25% in the 1980s to the current 39% [7] accounting for 22% of the total areas cropped in the country [8].

The most dominant cereal crop in Southern Africa is maize, but wheat is also grown to supplement the staple maize crop [9]. 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 [10]. 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 [11]. Wheat acreage increased from 0.5 t ha^{-1} in 1936 to over 3.5 t ha^{-1} in 2015 leading to 87% increase in wheat production and 20% improvement in the baking quality in the period between 1930 and 1990 [12]. It is mainly produced in the Western Cape, Free State, Northern Cape, North West and Mpumalanga provinces [13] with over 42% of the total 1.5 million ton wheat produced in 2019 coming 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 [9]. 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 [14]. 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% [15]. 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) [9].

The global population is projected to grow by 35% and reach 9.3 billion by 2050 [16], which will require an estimated 70% increase in food production mainly in wheat, maize, and rice (that occupy 58% of the annual crop area and account for 50% of the calories required) to cater for the future food demands [17,18]. Wheat production has to increase by 60% to ensure the global food security during projected period of surge in the world population [19]. Many of such production increases are expected to come from developing countries, where agricultural lands have to 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 is driving the variable and unpredictable weather conditions and increasing 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 [20], 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 [21]. 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 [22]. 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 [22]. Although such traditional area survey methods could be accurate, they are expensive, labour and time demanding, and do not produce accurate crop spatial distribution [23]. The advent of high spatial and spectral resolution remote sensing technology has, however, allowed the crop estimation data survey to evolve where satellite imageries are now used for agricultural land classification and estimation of acreages to be planted or harvested and has become a popular tool of choice for crop production 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 [24]. 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 [24]. 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 for 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 will particularly focus on crop-phenology based classification using temporal and spatial remote sensing satellite data.

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 (Figure 1). Reitze is located in th north-eastern part of the provicne and experiences a humid-subtropical climate with average annaul precipitation in region ranging from 300 - 900 [25]. It is predominatly planted with winter weat from late July to early August and with yellow maize from Ootober depending on the onset of rainfall.

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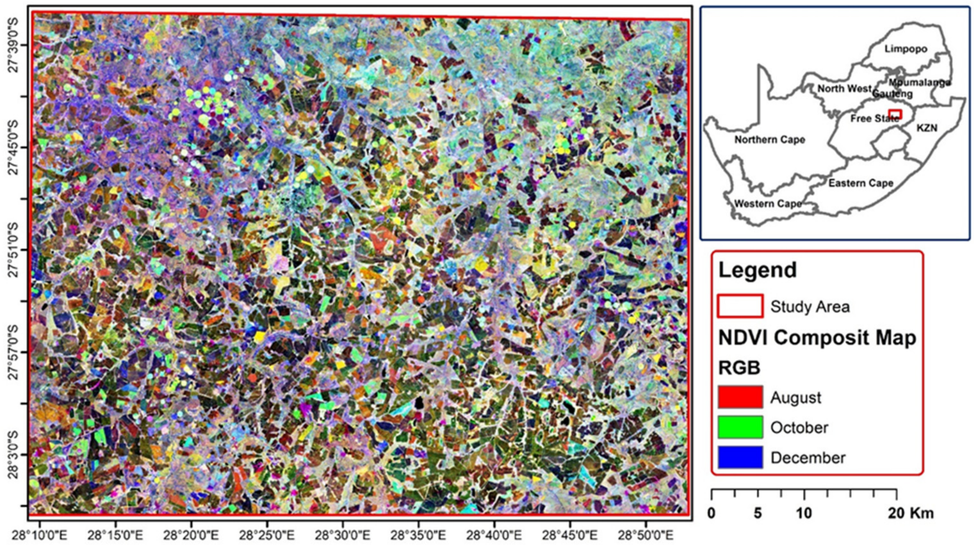

Figure 1. Sentinel 2 NDVI composite map of the study areas in Reitz, Free State Province, South Africa.

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 (Figure 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.

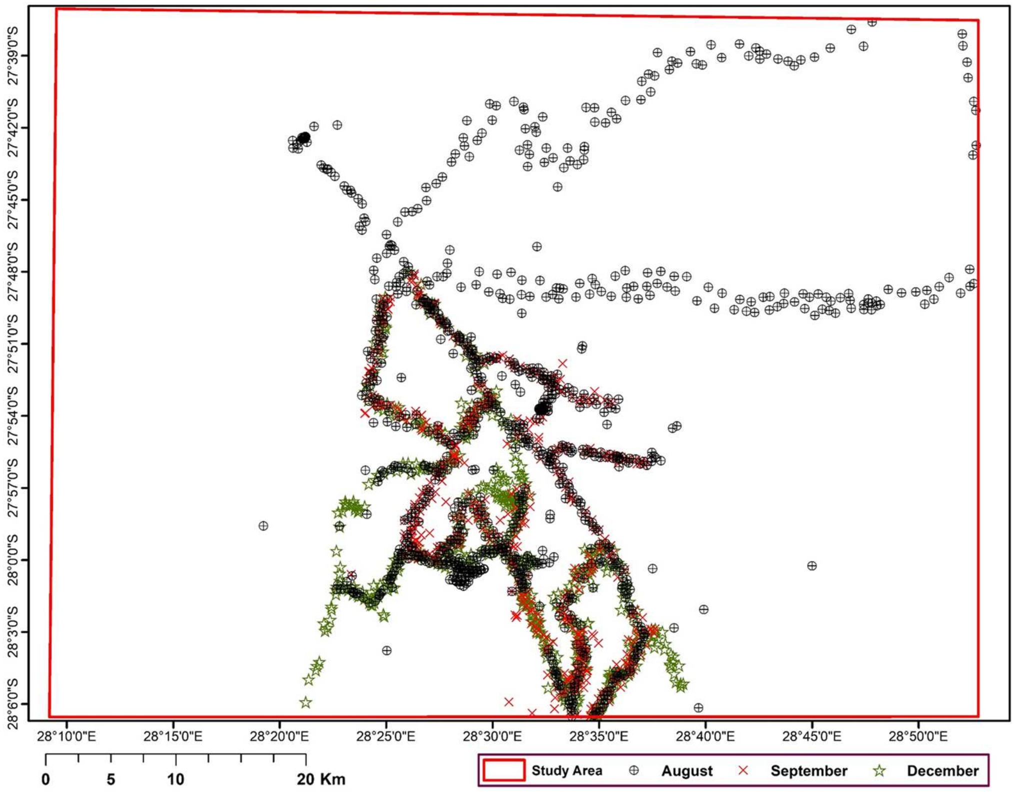

Figure 2. Ground-truthing Global Positioning System (GPS) points collected during the growing season of winter wheat in August, October, and December.

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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) classification algorithm and the classification accuracy was computed in a confusion matrix table. The entire winter wheat dataset obtained from 130 farms were also clustered into groups from the NDVI time series values averaged from 14 days stretching from August to December of the growing season to determine the optimum number of k-mean cluster using Iso cluster unsupervised classification algorithm on R software.

2.4. Plant Phenology

The most common phrenological stages of winter wheat 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) [26].

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

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 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 (Figure 4).

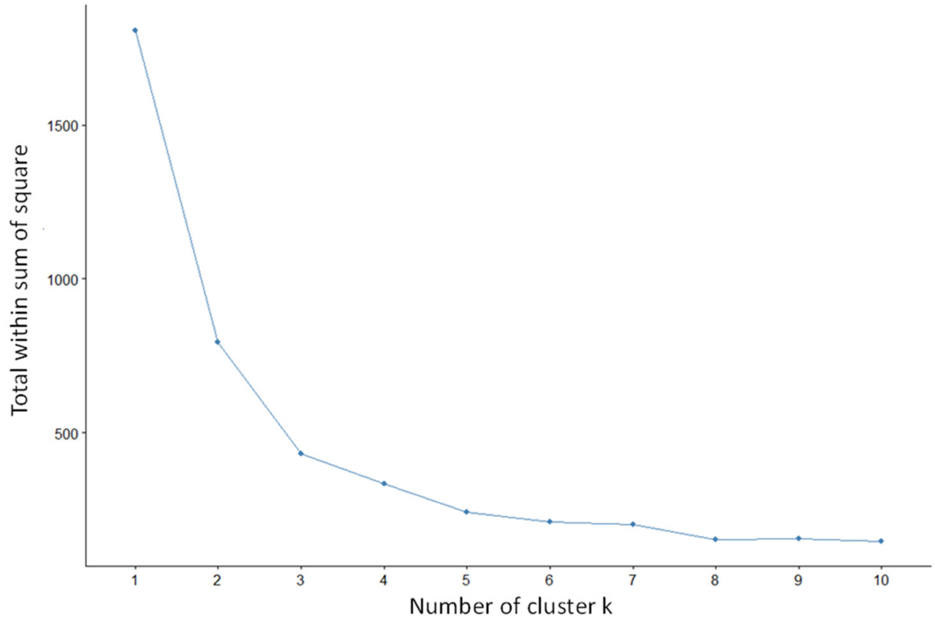

Figure 4. Elbow method used to determine the optimum number of clusters required to group the datasets into based on their similarity. .

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

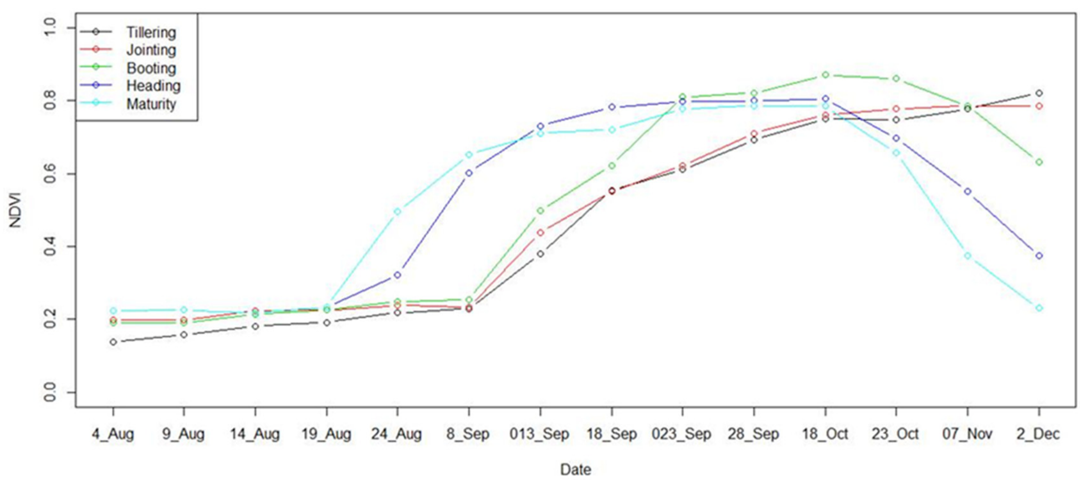

Figure 5. NDVI of winter wheat during the growing season from Aug- December 2020 in Reitz, Free State Province.

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 (Figure 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, at clustering group of 3 no overlap was observed between Tillering, Heading and Maturity.

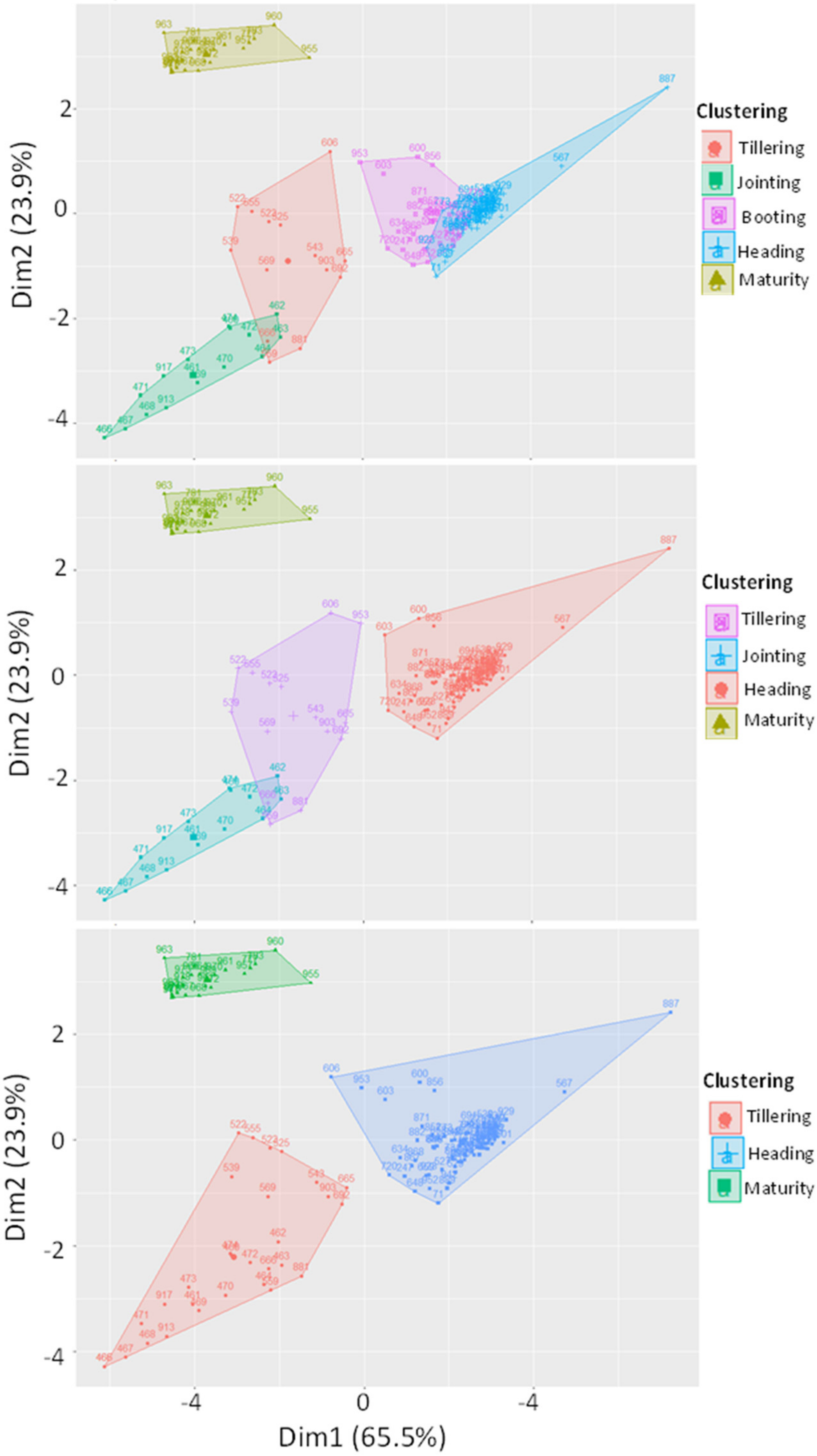

Figure 6. Unsupervised classification of winter wheat dataset using K-mean clustering algorithm.

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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.

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%**

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 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) crop stages 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) stage 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.

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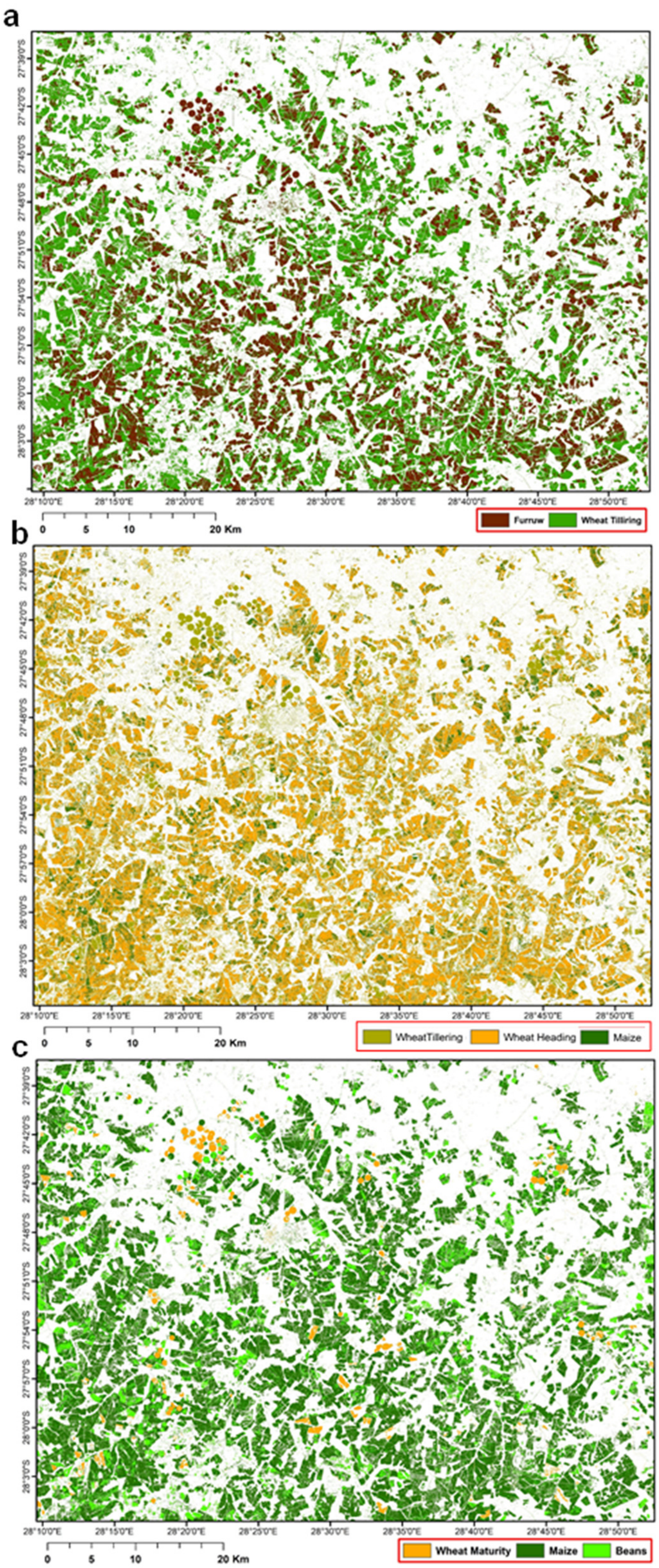

Figure 7. Classification map of winter wheat using Sentinel 2 satellite data with Random Forest algorithm for August, October, and December months of the crop-growing period in Reitz, Free State Province, South Africa.

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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%**

4. Discussion

Cultivation of winter wheat in Free State Province (Reitz) starts from mid of July to the first week of August and harvested in late December. The crops will germinate and grow 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 – 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 record of the crop growth stages. 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 (Figure 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 (Figure 5). The study areas, was however, distinctly clustered when the dataset was classified into 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 similar phenology-based classification of winter wheat using sentinel 2 [27]. It was also comparable to the overall accuracy of 84% reported for winter wheat phenology-based mapping using sentinel 1 [28].

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 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.

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 for crop yield forecast to ensure food security, but also a tool to support farm management and monitoring with scheduled irrigation and fertilizer application during critical stages of the crop growth stages. Sentinel 2 satellite imagery and the NDVI time series data can be used to effectively classify crops based on crop phenology.

5. Conclusions

Winter wheat crop was mapped using sentinel 2 and the random forest algorithm based on crop phenological stages over a period of three months (August, October, and December) and the highest classification overall accuracy of 83.58% was reported during the last growing season of winter wheat in December followed by October with overall accuracy of 78.14%. Nevertheless, the highest user's and producer's accuracy for the winter wheat was reported in October during the crop 'heading' stage, suggesting the best time to map winter wheat crop accurately during the growing season is the heading stage of the crop.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, Solomon Newete and Khaled Abutaleb; methodology, Solomon Newete and Khaled Abutaleb; software, Khaled Abutaleb; validation, Khaled Abutaleb and Solomon Newete; formal analysis, Khaled Abutaleb; investigation, Solomon Newete and Khaled Abutaleb; resources, Solomon Newete; data curation, Solomon Newete and Khaled Abutaleb; writing—original draft preparation, Solomon Newete; writing—review and editing, George Chirima, Katarzyna Dabrowska-Zielinska and Radoslaw Gurdak; visualization, Solomon Newete and Khaled Abutaleb and Katarzyna Dabrowska-Zielinska; supervision, George Chirima; project administration, Solomon Newete; funding acquisition, Solomon Newete.

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