

Spatial Intelligence





The Mapping of Agricultural Commodity Production and Infrastructure in the Western Cape Province

FINAL REPORT PART 1 – DELIVERABLE 1 AND 3 29 FEBRUARY 2024

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1 INTRODUCTION

The purpose of this document is to provide Part 1 of the Final Report for the Mapping of Agricultural Commodities Production and Infrastructure in the Western Cape Province (Bid 910 – 2022/2023). As per the Terms of Reference (TOR) the following is the anticipated deliverables for the project:

- **Deliverable 1** Mapping, geo-referencing of crops and rural agricultural infrastructure
- **Deliverable 2** Value of agricultural production in the Western Cape
- **Deliverable 3** Agro-processing & related infrastructure and facilities
- **Deliverable 4** Agricultural strategic analysis & business reporting

The final report will be submitted as two parts i.e. Part 1 and Part 2. In essence Part 1 will focus more on the methodology and the approach of collecting the baseline information for the project. Part 2 on the other hand will be more focused on the analysis and interpretation of the baseline information given current trends and market conditions as well as the comparison with the previous baseline studies and other relevant studies.

Given the deliverables above, it was decided that Part 1 would mainly focus on Deliverable 1 and 3 and Part 2 on Deliverable 2 and 4.

Part 1 and Part 2 of the Final Report should be read in conjunction with the 17 monthly reports that were submitted during the project period. These reports were as follows:

- Inception Report
- Literature Review Report
- Summary of the Summer Survey Report
- Remote Sensing Report 1 3
- 11 x Monthly Progress Reports

It is extremely important to work through all the project reports as the extent of this project is massive and over a 17-month period and therefore not all the information can be detailed in the Final Report.

This is the third iteration of the project in the Western Cape. The first project commenced in 2013 and concluded in 2014; the second project started in 2017 and was completed in 2018. The Western Cape Province is the only province in the country that has done multiple iterations of this baseline mapping project. There are only another two provinces that have each executed one iteration of the baseline mapping project - Gauteng Province and Limpopo Province. The true value of the baseline mapping project lies in the trends that are established over time i.e. comparing one study to an earlier iteration of the same study. These trends that are determined become invaluable for all involved in agriculture (policy makers, producers, input suppliers, financiers, insurers etc). SiQ is extremely proud of the fact to have been involved in all three iterations of this extremely important project.

Given the fact that this part of the Final Report (Part 1) will mainly focus on the methodology and the approach of the capturing and collection of the baseline data, it is important to note that

although the first and second iteration of this project (2013/2014 and 2017/2018) were similar as far as the implementation of the methodology and approach goes, the current iteration is significantly different in this regard. It is therefore important to highlight these differences and provide some insight into the potential impact that these changes could have on the results obtained for the project. These changes were requested in the TOR and were mainly driven by budget constraints for the project.

In order to obtain the data for this project a multi-disciplinary process involving various types of surveys, different personnel skill sets and different technologies ranging from aircraft to Geographic Information System software were utilised. This multi-disciplinary approach is key to the success of this project.

On a high level the approach that was followed involved getting a full understanding of the scope of the project through various meetings with stakeholders, sourcing of data that could attribute to the project (including satellite imagery data), creation of crop field boundaries for each potential arable field in the province, development of various questionnaires and computer aided capturing software, aerial, vehicle and telephonic surveys and finally a comprehensive data processing and quality assurance process.

2 METHODOLOGY AND APPROACH

2.1 What is different?

We have already mentioned that there was a significant difference with regards to how the field data was collected during the previous two iterations of the project when compared to this project. The essence of this difference lies in the following extraction from the TOR:

"Note: This iteration/update will require an increased reliance on remote sensing (RS) to distinguish annual winter cropping (e.g. wheat, barley, oats, triticale, Canola, lupins, lucerne/medics)."

This statement would translate to the fact that during the previous two iterations all farms in the province were overflown to capture information on all crops (every single potential field that could have been planted), livestock, agri-infrastructure (initial capturing and verification) as well as agri-tourism (initial capturing and verification). Whereas during this survey only statistical selected fields were overflown (as part of the Producer Independent Crop Estimates System (PICES)) and data was captured for these fields (in terms of crops) and then as much as possible information captured when routing from one statistical selected field to another. To enhance the number of field data collection points, two aerial observers (producers responsible for capturing the field data) were on board the helicopter (as opposed to one). Should one consider information from the past survey, it can be stated that although the statistical sample for the Western Cape of field data points that was captured during the aerial observation survey with two aerial observers onboard was 29 573 field observations.

It would be easier to interpret the difference of the previous two iterations in terms of the geographic coverage of the aerial observation when compared to the past survey geographic coverage. The two maps below provide insight into these differences:



It can therefore be stated that the bulk of the aerial observations was replaced by remote sensing and the classification of crop types by means of satellite imagery. This has many implications that will be discussed in more detail later in this document.

It should be noted that in terms of field observations and general field work that were conducted on this project, the approach was not only to conduct aerial-based surveys but also vehicle-based surveys. Vehicle-based surveys are generally far less effective than aerial observations, but they do provide the advantage of potentially being able to speak to a knowledgeable person on the farm. However, it has most definitely been found that compared to the previous iteration it has become increasingly difficult to gain access to farms in general and to get hold of farmers is becoming increasingly difficult. Security on farms is continuously being upgraded (due to constant exposure to criminal activities) and although this is good for safety on farms it does make vehiclebased surveys less effective. Loadshedding has a significant negative impact on the ability to get hold of farmers on their mobile devices as well as landlines. This again contributes negatively to gaining access to information from producers.

2.2 General

In broad terms the actions associated with this project can be summarised as follows:

- Project inception and meeting with the Department and Stakeholders to fully understand the scope of the Terms of Reference, and to obtain relevant information where available
- Sourcing of data that could attribute to the project, including extensive satellite imagery/aerial photography for mapping purposes and classification of crop types
- Data preparation and mapping (updating of crop field boundaries, crop categorisation and mapping of agricultural, livestock and agro-processing infrastructure, game farm boundaries etc.)
- Satellite imagery analysis to identify all irrigated annual summer crops
- Development of field questionnaire and survey software
- Communications campaign
- Summer aerial survey
- Winter aerial Observation Survey (PICES) as opposed to an Aerial Observation Census (as was done during the previous two iterations)
- Vehicle-based survey
- Extensive telephonic surveys and internet-based surveys due to the fact that the aerial survey was not a complete census of farms and fields
- Winter Crop Classification by means of satellite imagery processing and deep machine learning methods
- General area overview and trend interviews with information providers
- Telephonic vegetable survey
- Data processing, quality assurance and analysis of all spatial data
- Comparison report on alignment with other data sources
- Obtaining yield and market price information to compile value of agricultural production
- Agricultural strategic analysis and business reporting
- Production of final deliverables

Details on the abovementioned items are given in the following sections.

2.3 Stakeholder Meetings

At the start of the project various meetings were held with the Department of Agriculture, as well as with other stakeholders. During the project follow-up meetings were held with these and additional stakeholders on an ongoing basis.

The main purpose of these meetings was to:

- Ensure that the scope and requirements were fully understood
- Obtain information and data where available
- Get expert inputs in terms of planning
- Communicate with affected parties regarding access to properties for example farm access for the vehicle surveys
- Verify information obtained by means of the surveys

The Progress Report dated 28 February 2023 contains detail information regarding the meetings that were held with the numerous stakeholders in February 2023. Just as a summary the stakeholders are listed below (more detail information can be found in the report mentioned above):

- Cape Nature
- Hortgro
- Guava Association
- SAWIS
- SATGI
- OABS and Agri Western Cape
- Veterinary Services, Agro-processing and Aquaculture (WCDoA)
- Vinpro

Other stakeholders that were approach during the past couple of months for general trends in their industry and statistical information are:

- Hops, Tobacco and Novel Planted Pasture Specialists
- SANBI
- Subtrop
- SAPPA
- CGA
- Honeybush producers / researchers
- SA Olive

- SAMAC
- Chairmans of Dragon Fruit and Kiwi Fruit associations
- Berries ZA
- Persimmons / Almonds producers
- Potatoes SA, Tomato and Onion producers etc.

2.4 Sourcing and Analysing of Data (Spatial and Non-spatial)

Data that was sourced for the project included, but was not limited to:

- Previous survey deliverables (spatial and non-spatial)
- Agricultural Commodity Production & Infrastructure Data Set (previous flyover iterations mapping datasets) and reports
- WCG SDE GIS data as appropriate
- WCDoA GIS data standards
- Livestock Census (WCDoA Veterinary Services/CADIS)
- Strategic Plan of the Western Cape Department of Agriculture
- Land reform database AIMS (Spatial and non-spatial)
- Feedlots and Abattoirs Database WCDoA Veterinary Services
- Latest Farm portion and erf Cadastral Data Set WCDoA/DoTP of WCG 7.9
- STATS SA Agricultural Census
- Alien survey ARC
- Available digitised shade-netting footprint from the WCDoA
- Enclosure certificates for game farms from Cape Nature
- Latest aerial photography from NGI
- Sentinel-2 satellite imagery for the evaluation of the 2017 census data and for the 2023 winter crop type classification
- Benchmark information from various associations for example Hortgro, SAWIS, SATGI etc. These included annual reports and studies.

This data was used as follows:

- During the planning stage to indicate what could be expected where
- \circ $\;$ As input sources to some of the datasets produced during this project
- During the analysis stage to verify data

2.5 Cleaning, Updating and Categorisation of Crop Field Boundaries and Production of New Datasets

Although most of the datasets that were received required some form of cleaning or updating, only the most important datasets are discussed below.

2.5.1 Updating of Crop Field Boundaries

Although reference is made to the "updating" of crop field boundaries, this exercise was basically a re-doing of the crop field boundary layer for the Western Cape. This is due to the obvious fact that boundaries of fields have changed, but also more importantly due to the fact that the digitising of the boundaries was done on a much more accurate scale from the 2017/2017 census project. As agreed with the WCDoA the same scale was used for the updating of the crop field boundaries as was used during the previous iteration:

- Extensive crops: Scale 1:7 500 or better
- Horticulture, viticulture, shade-netting and tunnels: Scale 1:2 500 or better.

A digitising rules document that was compiled for the previous census project was extensively updated and used as guide by the team of digitisers to ensure that the same standards and rules were adhered to. (The 'Data Capturing Rules and Guidelines for field Crop Boundary Digitising' document can be found under Annexure A.)

All the updating was done from a combination of available photography, but with the 2022 NGI aerial photography being the main input. The area indicated below is the area that had 2022 imagery available whereas the rest of the areas were mostly digistised from Basemaps or the 2020 imagery.



Figure 1: Area covered with 0.25 GSD aerial photography of 2022

For the Summer irrigated crop "snapshot", in-season Sentinel satellite imagery dated January 2023 was used, together with classification data to determine fields with possible irrigation.

2.5.2 Crop Categorisation Process of Orchards, Viticulture, Vegetables, Herbs and Flowers

2.5.2.1 Orchard and viticulture crop categorisation process and determining stage of growth

After the updating of the crop field boundaries was completed, all the fields that were categorised as vineyards and orchards were extracted and the crop category captured during the 2017 / 2018 census survey compared to the observed crop category on the latest Google Earth / aerial photography. In instances where the crop category looked the same through visual inspection as it was with the 2017 / 2018 census survey, the crop type from 2017 / 2018 was assigned. If there was any uncertainty if the crop type was the same or if the crop type was correctly categorised with the 2017 / 2018 census survey or where there was a new crop planted, the field was flagged for a potential vehicle-based field verification to be done. With this process another phase of quality assurance regarding the digitising and updating of splits in fields was also done.

The following shapefiles were utilised to assist with the categorisation of the crops:

- SAMAC survey layer: this layer was provided by the Applied Agricultural Remote Sensing Centre (AARSC) in the UK who recently mapped macadamia orchards in South Africa.
- Summer aerial survey points captured (March 2023): these are points that were captured during the summer aerial survey for orchards, viticulture and other crops that could assist with the categorisation process.
- PICES survey points of the 2021 and 2022 winter surveys: these are points that were captured for orchards, viticulture and other crops during the winter PICES surveys of 2021 and 2022.

There were quite a lot of changes with regards to new fields, orchard crop type and changes from viticulture to orchards or vegetables. The following is an example of wine grapes in 2018 that were changed to Naartjies under shade-netting in 2023:



Figure: 2 Google Earth 2018



Google Earth 2023

With regards to determining the Stage of Growth, all crops that were observed during the 2017/2018 flyover and still the same crop were categorised as mature crops, where for crops that were different than the 2017/2018 flyover or new crops, the distinction made for the indexes of "newly planted" when the plants were extremely small and "intermediate" when the trees were larger.



Figure 3: Example of categorised orchards and viticulture

2.5.2.2 Vegetables, flowers and herbs categorisation process

All the digitised fields not planted with orchards and viticulture were scanned and checked for digitising errors, splits and missed fields during this process. With regards to vegetables, flowers and herbs, the crop category captured during the 2017 / 2018 census survey was compared to the observed crop category on the most recent Google Earth / aerial photography and if it looked through visual inspection like the same crop it was categorised as such. All fields that did not look like they have been planted with vegetables, flowers, or herbs any longer were changed to regular fields to be categorised with the remote sensing crop classification process. All possible new vegetables, flowers and herbs that were identified from the aerial photography were flagged for a potential vehicle field verification to obtain the crop type and producer contact details for a potential telephonic survey.

The following shapefiles were utilised to assist with the categorisation of the crops:

- Summer aerial survey points captured (March 2023): these are points that were captured during the summer aerial survey for orchards, viticulture and other crops that could assist with the categorisation process.
- PICES survey points of the 2021 and 2022 winter surveys: these are points that were captured for orchards, viticulture and other crops during the winter PICES surveys of 2021 and 2022.

2.5.3 Updating of Pivots and Splits for the Winter Aerial Survey (PICES) in August 2023

A process following the abovementioned updating of crop field boundaries was to update new pivots and splits visible on January to March 2023 Sentinel satellite imagery which needed to be updated for the Winter aerial survey (PICES) in August 2023.

2.5.4 Updating and Categorisation of Shade-netting

During the field crop boundary updating process all visible shade-netting was digitised from the available NGI aerial photography. After this the shade-netting was updated utilising Sentinel-2 summer in-season satellite imagery dated January 2023. This was done to be able to have a snapshot of all visible shade-netting up to end of January 2023. The latest shade-netting layer provided by the WCDoA was utilised in this updating process as well.

A new requirement as per the TOR was for categorising the type of shade-netting where possible and where there was uncertainty it was flagged for a potential vehicle field verification.

The following features had to be captured for the shade-netting:

Permanent / Seasonal	Type of Shade- netting structure	Type of cover	Colour
Permanent	Flat	Plastic or shade-nets	White, Grey, Black, Green, Blue, Other
Permanent	Pitched	Plastic or shade-nets	White, Grey, Black, Green, Blue, Other
Permanent	Dome	Plastic or shade-nets	White, Grey, Black, Green, Blue
Seasonal	Plastic strips	Plastic	Mostly white
Seasonal	Mini tunnels	Plastic	Mostly white

Table 1: Features captured for shade-netting

It should be noted that the bulk of the shade-netting (more than 96%) was the Flat Type Permanent shade-netting. There has been a significant increase in the number of hectares of shade-netting in the Western Cape. The table below provides a summary of these increases. It can be noticed that there has been an increase of 329% over the whole province in the area under shade-netting since the 2017/2018 census survey. The largest percentage (%) increase was found in Swellendam Local Municipality where the area increased by 1642% (from 26 ha to 447 ha). The Local Municipality that had the biggest increase in terms of the number of hectares added to that Local Municipality was Breede Valley with an increase of 1215 ha. Obviously, climate change is one of the factors playing a role in the increase in area under shade-netting. This will be discussed in more detail in Part 2 of the Final Report.

Table 2: Total permanent shade-netting and tunnel areas
captured - 2022/2023 vs 2017/2018

	Total Permanent Shade-netting and tunnels						
Local Municipality	2017/2018	2022/2023	% change				
Beaufort West	0.08	0.01	-89%				
Bergrivier	266.33	1 439.47	440%				
Bitou	4.38	3.59	-18%				
Breede Valley	172.62	1 387.25	704%				
Cape Agulhas	45.33	38.21	-16%				
Cederberg	153.29	1 318.43	760%				
City of Cape Town	66.49	134.41	102%				
Drakenstein	163.26	1 093.54	570%				
George	196.58	290.80	48%				
Hessequa	22.47	28.89	29%				
Kannaland	2.65	7.22	173%				
Knysna	2.37	14.09	495%				
Laingsburg	0.77	6.70	772%				
Langeberg	456.60	1 662.42	264%				
Matzikama	326.56	492.97	51%				
Mossel Bay	39.75	117.33	195%				
Oudtshoorn	7.05	8.89	26%				
Overstrand	95.40	93.85	-2%				
Prince Albert	4.80	6.81	42%				
Saldanha Bay	6.64	10.19	53%				
Stellenbosch	78.66	291.61	271%				
Swartland	334.71	1 287.29	285%				
Swellendam	25.65	446.92	1642%				
Theewaterskloof	102.42	502.74	391%				
Witzenberg	238.96	1 397.59	485%				
Total	2 813.79	12 081.20	329%				

A summary of the distribution of the crop categories planted under shade-netting is as follows:

Table 3: Distribution of crop categories planted under shade-netting

	% of Total
Crop Category	shade-netting
Berries	13%
Mature orchards	23%
Intermediate and newly planted orchards	26%
Mature Table grapes	27%
Intermediate and newly planted Table grapes	5%
Flowers and nurseries	2%
Vegetables and herbs	2%
Other crops	2%
Total	100%

Regarding new orchards planted in the past 5 years, 11% of the newly planted hectares has been planted under shade-netting.

The following map is indicating the location of the mapped shade-netting and tunnel structures:



Figure 4: Mapped Shade-Netting and Tunnel Structures

2.5.5 Updating of Tunnels

Tunnels were mapped as polygons as was done for the 2017/2018 census project, giving an indication of the total tunnel hectares.

2.5.6 Summary of Digitised Crop Field Boundaries

The following is a summary of the different field types that were digitised:

	2017	/2018	2022/2023		
Type of Field	Nr of Polygons	Total Hectares	Nr of Polygons	Total Hectares	
Fields					
Potential orchards			54 103	87 016	
Potential berries			2 161	2 391	
Potential viticulture			42 390	95 909	
Potential hops			133	466	
Potential flowers			2 049	2 850	
Potential Herbs			257	247	
Potential Vegetables			5 314	12 981	
Potential Vegetables (pivot)			642	7 946	
Potential Rooibos			5 329	78 982	
Potential Rooibos (pivot)			174	2 730	
Potential pivot irrigation			5 439	72 046	
Potential old fields			286	4 555	
Nurseries			1 900	1 095	
Other fields			175 160	1 611 952	
Total Fields	269 744	1 906 427	295 336	1 981 168	
Shade netting structures	1 887	2 494	3 256	12 081	
Outlines of tunnels/groups of tunnels	1 224	320	962	77	

Table 4: Total number of polygons and hectares digitised for crop field boundaries

The following table is a comparison of area planted with a certain crop over the past three census iterations:

Table 5: Comparison of area planted with berries and orchards over the past three census iterations

		Hectares Planted				
					%	Change in
					Change	area
					from	planted
Crop Category	Crop	2013	2017	2023	2017	from 2017
Berries	Blackberries	68	68	88	30%	20
Berries	Blueberries	465	824	1 762	114%	938
Berries	Raspberries	111	121	126	4%	5
Berries	Strawberries	202	176	389	121%	213
Total Berries		846	1 188	2 365	99%	1 177
<u> </u>		25	4 - 1	47	10/	
Citrus Fruit	Grapefruit	25	1/	1/	1%	0
	Lemons	831	2 042	2 8/4	41%	832
	Limes	156	202	1/6	-13%	-26
	Naartjies	3 066	6 315	9 380	49%	3 065
	Oranges	/ 625	/ /04	8 964	16%	1 260
Total Citrus Fruit		11703	10 280	21 411	52%	5 131
Nuts	Almonds	-	436	1 963	351%	1 528
Nuts	Macadamia Nuts	-	471	2 089	343%	1 617
Nuts	Pecan Nuts	-	214	602	182%	388
Nuts	Pistachio Nuts			10	100%	10
Total Nuts		-	1 121	4 665	100%	3 544
Pome Fruit	Apples	21 043	21 523	22 842	6%	1 318
Pome Fruit	Pears	11 328	10 711	11 023	3%	312
Total Pome Fruit		32 371	32 235	33 865	5%	1 630
Stopo Eruit	Apricoto	2 1 7 1	2 720	2 215	1 50/-	111
Stone Fruit	Charries	5 1/1	2 / 2 9	<u> </u>	-13%	-414
Stone Fruit	Noctarinos	1 696	1 515	1 075	20%	295
Stone Fruit	Peaches	7 809	6 848	5 763	- 16%	-1 086
Stone Fruit	Plume	5 767	5 644	5 651	0%	-1 000 8
Total Stone Fruit		19 / 37	16 804	16 156	- 10 /2	-727
Total Stolle I fuit		10 455	10 894	10 150	70	-737
Sub Tropical Fruit	Avocado	135	242	1 046	332%	804
Sub Tropical Fruit	Grenadillas	34	212	25	21%	4
Sub Tropical Fruit	Guavas	810	801	786	-2%	- 14
Sub Tropical Fruit	Mangos	29	111	127	15%	16
Total Sub Tropica	al Fruit	1 008	1 174	1 984	69%	810
Other Fruit	Dragon Fruit	- [9	19	108%	10
Other Fruit	Figs	347	370	296	-20%	-74
Other Fruit	Kiwi Fruit	-	10	97	867%	87
Other Fruit	Olives	6 167	6 207	6 244	1%	37
Other Fruit	Persimmons	455	354	327	-7%	-26
Other Fruit	Pomegranates	799	715	945	32%	230
Other Fruit	Prickly Pears	-	143	94	-34%	-48

		He	ctares Plan	ted		
					%	Change in
					Change	area
					from	planted
Crop Category	Crop	2013	2017	2023	2017	from 2017
Viticulture	Table Grapes	12 863	13 095	14 718	12%	1 622
Viticulture	Wine Grapes	108 070	91 221	80 593	-12%	-10 628
Total Viticulture		120 932	104 317	95 311	-9%	-9 006

Table 6: Comparison of area planted with viticulture over the past three census iterations

 Table 7: Comparison of area planted with grains, oil seeds and lupines over the past three census

 iterations

		Hectares Planted				
					% Change	Change in area
Crop Category	Сгор	2013	2017	2023	from 2017	planted from 2017
Grain	Barley	86 262	86 670	109 858	27%	23 188
Grain	Wheat	312 476	338 588	361 791	7%	23 203
Grain	Maize (summer)	4 388	3 783	6 175	63%	2 392
Oils seeds	Canola	71 865	90 523	134 426	48%	43 903
Lupines	Lupines	38 468	7 299	17 023	133%	9 724

The following table is indicating the area planted with mature trees and newly planted trees over the past 5 years:

Crop Category	Сгор	Mature Trees (older than 5 vears) (Ha)	% Mature Trees	Intermediate and Newly Planted Trees (Planted in	% Intermediate and Newly planted Trees	Total Area Planted (Ha)
Citrus Fruit	Grapefruit	17	99%	0	1%	17
Citrus Fruit	Lemon	1 724	60%	1 150	40%	2 874
Citrus Fruit	Lime	158	90%	18	10%	176
Citrus Fruit	Naartijes	4 802	51%	4 577	49%	9 380
Citrus Fruit	Oranges	6 432	72%	2 532	28%	8 964
Total Citrus Fruit	[· · · · · · · · · · · · · · · · · · ·	13 133	61%	8 277	39%	21 411
Nuts	Almonds	332	17%	1 631	83%	1 963
Nuts	Macadamia Nuts	294	14%	1 795	86%	2 089
Nuts	Pecan Nuts	210	35%	393	65%	602
Nuts	Pistachio Nuts	-	0%	10	100%	10
Total Nuts		836	18%	3 829	82%	4 665
			-			
Pome Fruit	Apple	18 843	82%	3 999	18%	22 842
Pome Fruit	Pear	9 244	84%	1 780	16%	11 023
Total Pome Fruit		28 087	83%	5 778	17%	33 865
Stone Fruit	Apricot	1 637	71%	678	29%	2 315
Stone Fruit	Cherries	128	28%	324	72%	452
Stone Fruit	Nectarine	1 190	60%	785	40%	1 975
Stone Fruit	Peach	4 258	74%	1 505	26%	5 763
Stone Fruit	Plums	4 067	72%	1 584	28%	5 651
Total Stone Fruit		11 281	70%	4 875	30%	16 156
			-			
Sub Tropical Fruit	Avocado	183	17%	863	83%	1 046
Sub Tropical Fruit	Grenadilla	12	48%	13	52%	25
Sub Tropical Fruit	Guava	679	86%	107	14%	786
Sub Tropical Fruit	Mango	100	79%	27	21%	127
Total Sub Tropica	l Fruit	974	49%	1 009	51%	1 984
Other Fruit	Dragon Fruit	7	39%	11	61%	19
Other Fruit	Figs	130	44%	166	56%	296
Other Fruit	Kiwi Fruit	3	3%	94	97%	97
Other Fruit	Olives	5 525	88%	718	12%	6 244
Other Fruit	Persimmons	284	87%	43	13%	327
Other Fruit	Pomegranate	504	53%	441	47%	945
Other Fruit	Prickly Pear	61	65%	33	35%	94

Table 8: Area planted with mature trees and newly planted trees over the past 5 years

Table 9: Area planted with mature vineyards and newly planted vineyards over the past 5 years

Crop Category	Сгор	Mature Trees (older than 5 years) (Ha)	% Mature Trees	Intermediate and Newly Planted Trees (Planted in	% Intermediate and Newly planted Trees	Total Area Planted (Ha)
Viticulture	Table Grapes	12 930	88%	1 787	12%	14 718
Viticulture	Wine Grapes	73 794	92%	6 799	8%	80 593
Total Viticulture	•	86 725	91%	8 586	9%	95 311



The following map is indicating the location of mature and intermediate/new tree plantings:

Figure 5: Location of mature and intermediate/new tree plantings

The following maps are indicating the location of some key commodities:



Figure 6: Table and Wine Grapes



Figure 7: Berries



Figure 8: Orchards



Figure 9: Grains and Oil Seeds



Figure 10: Vegetables



Figure 11: Hops, Tobacco and Teas

2.5.7 General Mapping Challenges

Due to the different approach with regards to the utilisation of remote sensing, a great deal of mapping of crops (not winter crops) had to be done from available imagery (satellite imagery as well as aerial and Google Earth photography). This section will just consider some of the challenges that was experienced with this type of mapping.

2.5.7.1 Overexposed and aerial photography older than 2022

In certain areas the quality of the NGI aerial photography was not so good and overexposed which in some instances made it difficult to see the outline of the crop field boundaries clearly especially in the drier areas like Laingsburg, Prince Albert, Oudtshoorn and Beaufort West. The available NGI aerial photography for Breede Valley, Mossel Bay, George, Knysna and Bitou was older than 2019 and the 2022 Basemaps had to be used which is extremely slow to extract and work with in the GIS software. NGI imagery for 2022 became available for Breede Valley after most of the digitising was completed whereas for Mossel Bay, George, Knysna and Bitou the NGI imagery for 2022 was not available in time.

2.5.7.2 Identification of crop type

Orchards and Viticulture:

Some of the crops were difficult to distinguish from one another when using remote sensing visual inspections and therefore there might be confusion between some of the following crops. This is not a comprehensive list but rather examples of crops that are not easy to distinguish from a mapping exercise: Apples/Pears, Nectarines/Peaches, Prunes/Plums, Oranges/Naartjies, Lemons/Limes, fynbos/honeybush/proteas and raisins were mostly included with table grapes. There might be a few confusions between wine and table grapes, but this is a small percentage.

Crops that are grown in the province in very small quantities (area planted) are also difficult to map in this way. These crops include crops such as kiwi fruit, dragon fruit and mangos. To obtain better results for these crops producers were contacted who assisted in the location of most of the new plantings they were aware of. There are, however, some fields that could not be mapped as they could not be found with the directions given.

Telephone calls were made, or emails sent of the areas of unknown crops to some knowledgeable producers or the producer of the actual farm, but not all responded or wanted to assist and therefore some of these fields are still unknown in terms of the actual crop planted on them.

Vegetables:

Most vegetables can be distinguished from other crops if it has the typical colour variation between the different strips of vegetables planted and the texture. For vegetables like potatoes however, it is almost impossible to distinguish a potato (under pivot irrigation) from a grain crop (under pivot irrigation). Potato fields/pivots might thus have been missed. A process was followed to try and identify potato pivots by visually inspecting in-season Sentinel imagery dated December 2022 and May 2023 in the Sandveld and Koue Bokkeveld areas to scan for green pivots that could potentially be potatoes or onions. During the December/May months potatoes and onions would clearly stand out with possible just planted pastures / lucerne/ medics and summer crops having the same colour. The summer grain pivots were identified with the summer aerial survey and removed and planted pastures / lucerne/ medics removed with the Remote Sensing / Artificial Intelligence / Machine Learning Processes. The remaining pivots were categorised as potatoes / onions.

It is also important to note that is difficult to distinguish between the different types of vegetables. In some instances, a pattern can be picked up for instance for onions and tomatoes or a grey colour for cabbages, but in general it is very difficult to determine the type of vegetable and a field verification required. If there was certainty with the assistance of field captured points, the type of vegetable was specified, otherwise if there was certainty that it was some kind of vegetable, it was just categorised as 'Vegetables'. Due to the fact that vegetables are being rotated it is not always easy to determine when or whether vegetables were planted in the relevant year. If there was thus any uncertainty if a field was a vegetable field, it was categorised as 'Possible vegetables'.

Flowers and herbs:

It is not possible to determine the type of herb or flower except for proteas with a visual remote sensing process. Herbs and flowers can sometimes even be confused with vegetables. The specific crop type for herbs and flowers can thus in most instances only be determined with a field verification.

2.5.7.3 Determining the stage of growth

The stage of growth was determined according to the size of the trees visible on the imagery that was available. There might thus be trees that appeared as newly planted on the older imagery that must in fact now fall under the intermediate index.

2.5.7.4 Continuous changes with crops being removed or changed

It was sometimes a challenge to keep up with the continuous changes taking place with fields being added and crops being removed or changed. The initial digitising was done on a specific year's imagery and the processes that followed often done on more recent imagery thus making a lot of additional updates necessary. All changes that were observed during the later processes were updated but not all areas were relooked at again and might still be as it was originally digitised from the older imagery. Some of the major changes were vineyards that were cleared to plant vegetables and to be replanted again as a vineyard. The same with pears and apples that were cleared and then often replanted with the same crop again. Some new orchards were recently discovered on the new Google imagery in areas where one would not expect an orchard. This was unfortunately after all the field survey processes were completed and the crop thus categorised as unknown.

2.5.7.5 Conclusion

It was found that utilising Google Earth with QGIS worked extremely well as in numerous areas the Google Earth imagery was clearer and of better quality than the aerial photography from NGI. The Google Earth imagery was in most cases more up to date (NGI was generally 2022) and furthermore the NGI imagery was overexposed in a many areas. Utilising Google Earth with QGIS might thus be the preferred method of digitising in future.

2.6 Mapping of Agro-processing and Livestock Infrastructure

2.6.1 General

The infrastructure mapping process entails the verification and updating of the captured points of the previous 2017/2018 census layer and the capturing of new points by utilising layers and data received from the WCDoA, other stakeholders and the Internet.

The separate mapping rules document that was used as a guide by all resources working on the project was updated to address enhancements made to the mapping process since the previous project. This document explains in detail what needed to be mapped and how it should be captured. (The 'Data Capturing Rules and Guidelines for capturing Agricultural Infrastructure and Agro-Processing' document can be found under Annexure B.)

The following datasets were received and utilised for verification and mapping purposes:

Abattoirs:

Georeferenced list from WCDoA Veterinary Services - these are all abattoirs that are now active and registered.

Agro-processing plants:

List from WCDoA Agro-processing division +- 300

Georeferenced WCDoA Veterinary Services' list with livestock Agro-processors

Aquaculture:

Shapefile of aquaculture facilities that was confirmed by Dr Ferdi Endemann (WCDoA)

Auction facilities:

Georeferenced list from WCDoA Veterinary Services

Cellars:

List of 30 cellars from WCDoA Agro-processing division

Georeferenced wine cellar, olive cellar, distillery, brewery lists from Riaan Nowers (WCDoA)

Feedlots:

Georeferenced list from WCDoA Veterinary Services

<u>Livestock infrastructure:</u>

Georeferenced Census (2020 – 2022) from WCDoA Veterinary Services

Georeferenced Rabbits census (2018-2021) from WCDoA Veterinary Services

Georeferenced Alpaca census (2018-2021) from WCDoA Veterinary Services

Georeferenced SiQ livestock Census data 2017/2018

- Silos:
 - SAGIS list with commercial silos and mills

The complete province was covered during this exercise and the typical zoom scale for this action was in the region of 1:1 000. This extremely low zoom scale requires a great deal of concentration and a large effort to work through the whole of the province, and as such a grid-block approach was followed where a mapper worked through his area one block at a time.

The verification of this infrastructure was done by utilising the internet, Google Earth, Google Maps, Streetview and telephonically. Google maps and Streetview were used extensively in the capturing of Agro-processing infrastructure around the towns. During the reduced aerial and vehicle survey a number of infrastructure points and livestock information was captured and also incorporated into the dataset.

2.6.2 Quality Assurance

A Quality Assurance document was compiled to ensure that all the necessary quality checks were performed on the captured infrastructure. (The 'Quality Assurance for Agricultural Infrastructure and Agro-Processing' document can be found under Annexure C.) The first step in the Quality Assurance process was to standardise all the attributes. Some of the quality assurance being performed was spatial queries to ensure that all available lists provided by the WCDoA, and other stakeholders were considered. Cross-check queries were also performed between the infrastructure captured points and the field boundaries. Additional lists were continuously sourced to ensure that no infrastructure was missed. Whilst being very zoomed in on certain areas during the quality assurance process of the crop field boundaries, infrastructure observed was also captured in certain areas which was also utilised for quality assurance purposes.

Google maps and Streetview were used extensively during the Quality Assurance process.

2.6.3 Summary of Captured Data

Comparing the captured livestock infrastructure with the data captured of 2017/2018 it will be noticed that there is often a reduction in the number of infrastructure. The reasons for these lower figures are noted below the table of figures.

A summary of the livestock infrastructure captured compared to the 2017/2018 data is as follows:

LOCAL	NO OF		NO OF LIVESTOCK AUCTION FACILITIES		NO AQUACULTURE		NO OF CHICKEN BATTERY STRUCTURES						NO OF PIGGERIES	
MUNICIPALITY	2017	2023	2017	2023	2023	2023	2017	2023	2017	2023	2017	2023	2017	2023
Beaufort West	12	11	2	-	0	0	0	0	0	0	1	2	1	1
Bergrivier	2	2	3	2	0	0	15	23	29	24	4	4	14	9
Bitou	1	1	1	-	0	0	13	13	9	2	0	0	1	1
Breede Valley	3	3	1	1	1	1	227	234	10	9	0	1	2	1
Cape Agulhas	3	2	1	2	0	0	6	0	46	21	5	10	0	8
Cederberg	6	5	0	-	0	0	0	0	6	4	0	1	4	6
City of Cape Town	7	4	1	2	3	3	380	358	23	11	3	2	8	8
Drakenstein	6	6	4	2	8	7	401	420	19	7	1	1	9	4
George	3	3	2	3	5	6	42	29	54	44	2	2	12	6
Hessequa	7	4	2	1	0	0	10	19	141	110	5	1	2	1
Kannaland	1	1	0	-	0	0	0	0	17	4	6	0	0	1
Knysna	4	3	0	-	0	0	3	0	23	18	0	0	1	1
Laingsburg	2	2	0	-	0	0	0	0	0	0	0	2	0	-
Langeberg	3	3	0	-	4	4	16	13	30	22	8	6	2	2
Matzikama	2	2	1	1	1	2	0	0	0	1	0	0	0	-
Mossel Bay	4	4	1	2	1	1	4	9	57	51	0	0	1	1
Oudtshoorn	4	3	2	3	0	0	0	0	30	5	3	2	3	5
Overstrand	1	0	2	2	6	12	64	55	17	23	0	0	2	-
Prince Albert	1	0	0	-	0	0	0	0	0	1	0	0	0	-
Saldanha Bay	2	3	1	1	13	22	32	52	11	3	3	1	2	1
Stellenbosch	1	0	1	-	5	6	91	78	10	3	0	0	18	5
Swartland	5	5	3	3	1	1	309	301	51	43	7	6	34	26
Swellendam	5	4	2	1	0	1	9	16	102	74	0	0	0	4
Theewaterskloof	4	3	3	-	1	1	56	67	55	32	6	9	5	3
Witzenberg	2	1	2	2	1	1	58	56	12	8	1	2	4	5
TOTAL	91	75	35	28	50	68	1736	1743	752	520	55	52	125	99
	Note 1		te 1 Note 2				Note 3		Note 4		Note 5		Note 6	

Table 10: Livestock infrastructure captured compared to the 2017/2018 census data

Note 1 - There are less abattoirs registered with WCDoA in 2023 than in 2017.

Note 2 - Incorrect structures were mapped as auction facilities in 2017/2018 which is the main reason for the lower figure in 2023.

Note 3 - Incorrect structures were mapped in 2017 which were removed in 2023 and there were also chicken batteries that closed.

Note 4 - Many incorrect points were captured as dairies in 2017/2018 which were removed as they could not be verified in 2023.

Note 5 – Only larger feedlots were mapped.

Note 6 - In 2017/2018 structures were categorised as piggeries that were just for a couple of pigs being farmed with. These were mapped as 'Other infrastructure' in 2023. Incorrect structures that were mapped were also removed from the 2017/2018 data.

In addition to the abovementioned livestock infrastructure, 9728 points were captured for the infrastructure of cattle, sheep, ostriches, goats, alpacas, emus and rabbits.



The following map is indicating the location of the mapped livestock infrastructure:

Figure 12: Mapped Livestock Infrastructure

A summary of the agro-processing infrastructure captured compared to the 2017/2018 data is as follows:

LOCAL	PACKHOUSES		FRUIT PACKERS		COOL CHAIN FACILITIES		FRUIT PACKERS AND COOL CHAIN FACILITIES		MILLERS		TEA PROCESSING		OTHER AGRO- PROCESSING	
MUNICIPALITY	2017	2023	2017	2023	2017	2023	2017	2023	2017	2023	2017	2023	2017	2023
Beaufort West	0	0	0	-	1	-	0	-	0	-	0	-	0	4
Bergrivier	60	66	9	7	5	3	10	6	2	1	4	9	15	15
Bitou	4	3	0	-	3	-	0	-	0	-	0	2	1	7
Breede Valley	160	178	3	6	4	4	1	2	0	-	0	-	9	10
Cape Agulhas	2	10	0	1	0	-	0	-	0	-	1	1	4	4
Cederberg	59	78	3	2	1	1	13	11	1	1	44	61	14	8
City of Cape Town	5	3	0		33	40	3	-	10	8	0	4	94	212
Drakenstein	82	99	24	17	5	2	14	12	6	5	1	-	19	40
George	36	36	3	4	0	-	9	7	2	1	0	-	13	22
Hessequa	5	6	0	-	0	-	0	-	1	1	0	-	9	8
Kannaland	27	23	1	1	1	-	0	-	1	1	0	-	2	4
Knysna	3	3	0	-	1	-	0	-	0	-	0	-	0	7
Laingsburg	21	17	1	1	0	-	0	-	0	I	0	-	1	1
Langeberg	38	65	4	2	0	-	13	10	1	1	0	-	28	25
Matzikama	16	21	1	-	2	1	1	1	0	I	24	26	3	3
Mossel Bay	7	11	0	-	0	-	0	-	0	1	1	1	8	7
Oudtshoorn	7	9	0	-	0	-	1	1	6	4	0	-	3	11
Overstrand	8	8	0	-	1	-	0	-	0	I	0	-	15	14
Prince Albert	13	1	0	-	0	-	0	-	0	-	0	-	3	2
Saldanha Bay	1	1	0	-	0	-	0	-	0	-	0	-	17	10
Stellenbosch	67	88	1	-	2	-	12	11	0	-	0	-	14	24
Swartland	28	43	1	2	2	-	8	4	10	4	0	-	5	13
Swellendam	22	33	2	4	0	-	3	1	1	-	0	-	3	3
Theewaterskloof	166	147	3	3	2	-	33	29	2	2	0	-	17	13
Witzenberg	145	199	32	17	1	4	32	30	1	-	0	-	4	15
TOTAL	982	1148	88	67	64	55	153	125	44	29	75	104	301	482

Table 11: Agro-processing infrastructure captured compared to the 2017/2018 census data

Please take note of the following:

- Some of the agro-processing facilities were incorrectly categorised during 2017/2018 and moved to different categories in 2023.
- For some larger facilities 2 points were captured in 2017/2018 where in 2023 only one point was captured.
- Some agro-processing facilities were captured as packhouse in 2017/2018 due to little information available and now correctly categorised as agro-processing.
- In 2017/2018 there was a couple of cool chain /fruit packer combinations that was now changed to agro-processing due to other functions also performed by the facility.
- Incorrectly captured points were removed from the 2017/2018 data that could not be verified in 2023.
- There has been a 20% increase in the total of fruit packers, cool chain facilities and other agro-processing facilities mapped compared to the 2017/2018 census and a 17% increase in the total packhouses mapped.



The following map is indicating the location of the Agro-processing facilities:

Figure 13: Mapped Agro-Processing Facilities

A summary of the Breweries, Distilleries, Olive and Wine Cellars, Olive Cellars and Wine Cellars captured compared to the 2017/2018 data is as follows:

Table 12: Breweries, Distillerie	s, Olive and Wine	Cellars, Olive	Cellars and V	Vine Cellars ca	ptured
compared to the 2017/2018 ce	ensus data				

			DICTU		OLIVE AN	ID WINE	OLIVE C	ELLARS	WINE CELLARS		
LOCAL	DREVV	ERIES	DISTILLERIES		CELL	ARS					
MUNICIPALITY	2017	2023	2017	2023	2017	2023	2017	2023	2017	2023	
Beaufort West	0	-	0	-	0	-	1	1	0	0	
Bergrivier	0	1	0	1	0	-	2	2	5	6	
Bitou	1	2	0	-	3	-	1	1	3	9	
Breede Valley	1	1	3	3	0	-	4	6	38	38	
Cape Agulhas	0	1	0	-	0	-	0	-	7	9	
Cederberg	1	2	0	-	1	1	0	-	4	6	
City of Cape Town	31	25	2	4	4	3	2	3	50	53	
Drakenstein	5	8	4	4	5	5	12	11	73	106	
George	0	1	0	-	0	-	0	-	3	3	
Hessequa	0	-	1	1	0	1	0	2	3	3	
Kannaland	0	-	0	-	1	1	1	1	9	9	
Knysna	3	2	0	-	0	-	0	-	0	0	
Laingsburg	0	-	0	-	0	-	1	-	0	0	
Langeberg	3	3	2	3	1	2	8	6	63	70	
Matzikama	1	1	0	1	0	-	0	-	14	16	
Mossel Bay	1	1	0	2	0	-	0	-	0	1	
Oudtshoorn	0	-	0	-	0	-	2	3	1	6	
Overstrand	0	4	0	-	2	2	1	1	20	23	
Prince Albert	0	-	0	-	0	-	3	3	3	1	
Saldanha Bay	1	2	0	-	0	-	0	-	0	0	
Stellenbosch	10	10	1	2	12	12	7	7	197	254	
Swartland	3	2	0	-	1	3	2	3	26	31	
Swellendam	0	1	0	2	0	-	0	1	5	4	
Theewaterskloof	2	3	1	2	1	2	2	2	34	42	
Witzenberg	0	1	0	-	3	2	3	2	19	25	
TOTAL	63	71	14	25	34	34	52	55	577	715	

The following map is indicating the location of the mapped Breweries, Distilleries, Olive and Wine Cellars, Olive Cellars and Wine Cellars:



Figure 14: Mapped Breweries, Distilleries, Olive and Wine Cellars, Olive Cellars and Wine Cellars

2.7 Mapping of Game Farms

Very productive discussions were held with Cape Nature in February 2023 which resulted in obtaining a spatial layer of Nov 2021 with the Game Enclosure Certificates that has been mapped on their side. This layer was used as a base layer to add any additional game farms and new data to. From the data that was received from Cape Nature, 619 properties with game enclosure certificates were spatially mapped and 16 properties had no spatial reference. Unfortunately, only one of these unmapped properties could be mapped after various searches. The types of game observed at these registered game farms that was also received from Cape Nature was also linked to the data.

A meeting was arranged by WCDoA with SANBI who was prepared to share spatial data with declared Biodiversity Stewardship sites and research data from one of their colleagues PHD's thesis with us. Riaan Nowers from the WCDoA also provided a list with game farms that was a combination of game farms that was mapped as agri-tourism infrastructure during the 2017/2018 census project and new game farms he kept record of over the past 5 years. These datasets together with the data captured during the 2017/2018 census and current aerial and vehicle surveys were used to fill in missing detail. Internet searches were also performed to search for additional game farms. In total only seven new game farms were added whilst attributes and boundaries of the original 619 registered game properties were updated.



The following map is indicating the final mapped game farms after consulting all the sources:

Figure 15: Mapped Game Farms from Cape Nature Game Enclosure Certificates and Other Sources

No further updates were received from Cape Nature after the 2021 dataset.

Some innovative ways of trying to find additional game farms were also implemented. When driving along a rural road game farms are usually easily distinguished by the fencing that is used to ensure that the game on the farms stays within the boundaries of the particular farm. Google Earth Streetview was used extensively to assist with the finding of some of the additional game farms. Below are some of the screenshots that were taken during the mapping.



Figure 16: Google Earth Streetview images of some of the game farms investigated



Figure 17: Typical game farm fencing

2.8 Development of Field Questionnaires and Survey Software

Various questionnaires were used during the project as follows:
- Vehicle-based survey questionnaire: To obtain information from producers in the field, especially in the event where it was not possible to obtain this information during the aerial survey
- Aerial-based capturing screen: To capture crop type and infrastructure as well as other required information
- General area wide questionnaire: To obtain information in specific regions on items such as farming practices, emerging trends etc.
- Telephonic vegetable questionnaire: To obtain information on vegetable production.

For all the field questionnaires a data capturing software platform was developed. This was used to capture data directly onto an electronic device or for some questionnaires to convert a paperbased field questionnaire into an electronic platform.

2.8.1 Aerial-based surveys

For the aerial-based surveys, a highly customised ArcPad implementation was used. This system also has the ability to show a moving map display, which the observer uses to orientate himself. An example screen of this system is shown in the following picture:



Figure 18: Moving map with digitised fields

Capturing of information is done directly onto the system, and provision is made for all the commodities that can be captured, as shown in the image below.

Storey & CREADURDED	SISJICKS T CAPTURE NR	,								×	×
Str. 1	GROP: GRO	ENTE				25% E 50% E 78 025 No E 03 No E 11	95 P 1009 Na E 2 Na	E 54 Ha	ID:	260001	
22	KORING	KANOLA	ROOIBCS	1.689W/MEDICS	WINDRUF	AGP WEDDING	NATRI VELD	OULAND	BRARK	STOPPELS	
	GARS	LUPINE	KLEINGRANE	KS WEIDING	TATELDRUF	AGP WO NEER	ONITUD	HOPS		PV	\sim
	KOROG	HAMERMOUT	VOERGARS	TABAK	ANDER	0469390	PARHUS	RUNWAY	1	GASTEHUIS	
	BLOMME			E TON	NEL	NELKOLESTE VLEISBERSTE SKAPE	0-10 11-50	SL+ Feedlet	Inactive		
1	sponter			■ □ sca □ sca	NINETAWEEKH	VARKERY BORKE PERCE DOWNE MUR.					$\sim \langle \lambda \rangle$
	VIDCTE					ALPACA / LLANA WILD	221				
5	DRCELAND	BESPRO	E DNB	DENO BES	\$PROET	HOBIOERSEERS HOBIOERSELAG VOLSTRUEE					
	E VLDED	E SPRINK	EL ERV DL ERV	ORPY IDER		E NO LIVESTOCK				E smins-runt	
							•		06	GANDEL	
	@⊗≓	•							_		$\mathcal{K} = \mathcal{K}$
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											3257115185846 \$11500 V

Figure 19: ARCPad capturing screen

The capturing software that was used for the aerial survey for the 2017/2018 agricultural census was updated and fields removed that were not relevant for this survey and new fields added for additional crops and infrastructure that had to be captured like the type and colour of shade-netting, types of novel planted pasture species etc.

🔶 CAPTURE INFO)								×
CROP:				г	25%	% ₽ 100%		ID: 2	00031
MIELIES	SOYABONE	SORGHUM	SONNEBLOMME	AGP WD MEER	ANDER	STOPPELS	BRAAK	ONKRUED	OU LAND
TAFELDRUOF	WYNDRUJF	BLUEBERRY	ТАВАК	AGP WD 1	ONBEKEND			NIE GEMAP	NATRL VELD
ROOBOS	HONEYBUSH	BUCHU	HOPS	JUSERN/MEDICS					
BLOMME			IT SKAD	DUNET/KWEEK NEL	PLASTIC STRIP BOORD	I NOVEL			ONAKTIEF
GROENTE								ELKERY EESVOERKRAAL KAAPVOERKRAA	
VRUGTE								ARKERY LAGHOENDERS IERPLAAS ALD	
								г	SPRING-PUNT
				•				ок	CANCEL
®⊗ ∌									

Figure 20: Data capturing software screen

🔶 CAPTURE INFO)									>
CROP: BLOM	IME				25% 🗆 50%	□ 75%	₩ 100%		ID: 4	200031
MILLES	SOVABONE	SORGHUM	SONNEELOHME	AGP WD MEER	ANDER		STOPPELS	BRAAK	ONKRUID	OU LAND
TAFELDRUIF	WYNDRUDF	BLUEBERRY	TABAK	AGP WD 1	CNREXEND	_			NIE GEMAP	NATRL VELD
ROOTBOS	HONEYBUSH	BUCHU	HOPS	.USERN/MEDIC						
BLOMME	ANDER		E SKA	DUNET/KWEEK NEL	E PLASTIC STRE	P	NOVEL	-		ONAKTIEF
GROENTE	ONBEKER KOLJAND KRUIF	ND ER		PLASTIC				E M E B	IELKERY EESVOERKRAAL KAAPVOERKRAA	L
VRUGTE	PROTEAS ROSE TURKSVY	к ;		PITCHED DOME MINI TUNNEL NORMAL TUNN	C GREY TRANSPARENT COTHER				ARKERY LAUHOENDERS IERPLAAS	
DROELAND	BESPRO	EI ONB	KEND BE	SPROET					WLD	
VLOED	E DRAGLIN	E E MK	ORD OPPY					T YOER	r	SPRING-PUNT
IT DRIP	ET KANT-RO	L TAN	DER	•					ок	CANCEL
				•						

Figure 21: Data capturing software with dropdown list

2.8.2 Vehicle-based Surveys

For the vehicle-based surveys, an ArcMap-based capturing system was used. Feature templates were developed for efficient and accurate data capturing and all necessary data was provided in the ArcMap document. The system was connected to a Bluetooth GPS to be able to show a moving map display. An example screen from this system is shown in the following picture.



Figure 22: Vehicle-based survey capturing screen

2.8.3 Telephonic General Area Wide and Vegetable Surveys

The telephonic surveys were first concluded on paper and then transferred into an electronic format by means of a web-based system. An example screen of such a web-based input form is shown in the picture below.

Point Nr: 57

PRODUCER DETA	ILS		
Name	Producer name	Date:	2018/04/25
Telephone nr		Surveyed	Refusal
Cell phone nr		Not surveyed	Respondent could not be reached
E-mail address			Incorrect contact details

CHOP OPEN AIR TUNNELS SHADE NETTING Production Hectares planted Yield planted Trickl (Ton/ha) Production (Ton) Hectares planted Yield (Ton/ha) Production (Ton) Production (Ton) A drappets 40 45 1800 0	1) TOTAL VEGETABLES FOR THE YEAR 1 MARCH 2017 TO 28 FEBRUARY 2018												
CHOP Hectares Yield Production Hectares Yield Production Hectares Yield Production Hectares Yield Production Itemated (Ton) Itemated Itemated <th< th=""><th></th><th></th><th>OPEN AIR</th><th></th><th colspan="3">TUNNELS</th><th>S</th><th>INDE NETTI</th><th>NG</th><th></th><th>OTHER</th><th></th></th<>			OPEN AIR		TUNNELS			S	INDE NETTI	NG		OTHER	
Matappets 40 45 1800 0	CROP	CROP Heotares Ye planted (Ton		Production (Ton)	Heotares planted	Yield (Ton/ha)	Production (Ton)	Hectares planted	Yield (Ton/ha)	Production (Ton)	Heotares planted	Yield (Ton/ha)	Production (Ton)
Agurties Image: Section of the sect	Aartappels	40	45	1800	0	0	0	0	0	0	0	0	0
Artisjokke Image: state st	Agurtjies												
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Beet Image: section of the section	Aspensies												
Blanstaal Image: Second Se	Beet												
Biomkcol Image: Second se	🔲 Blaarslaal												
Botterskarsie Image: Second Secon	Blomkcol												
Brokkol Image: Constraint of the second	Botterskorsie												
Brusselse spruite Image: Spruite Im	Brokkali												
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Knoffei Image: Strategy and St	Groen bone												
Komkommer Image: Source of the state of the	Knoffel												
	Komkommer												
	Kool												

Figure 23: Vegetable survey input screen

2.9 Aerial survey

2.9.1 General

The aerial observation survey consisted of two surveys. The first survey was the summer crop survey (13 - 18 March 2023) and the second survey was the extended PICES winter crop survey (14 - 24 August 2023). These surveys will be described in more detail below.

2.9.2 Summer Crop Survey

To focus and refine the summer survey and to determine the fields to be included for the summer aerial survey, a satellite imagery analysis was carried out to identify all fields that were potentially irrigated during the summer crop season. To increase efficiency, it was also important to try and exclude crops that were not summer grain or target annual crops; for instance, planted pastures, lucerne and vegetables.

To do this determination, it was necessary to use a time-series of Sentinel 2 satellite imagery, from which NDVI and NDMI imagery were derived. The goal was to identify the possible fields to be surveyed by comparing the NDVI and NDMI indices per field for specific periods. This process was supplemented by using information that was obtained from knowledgeable industry contacts, as well as historical data.

For the summer crops a full aerial survey was required according to the Terms of Reference. The summer aerial survey took place from around 13 – 18 March 2023 where the possible summer crop fields that were identified with the abovementioned automated process were overflown and the summer crops (maize, hops, tobacco, novel planted pasture species or other) identified. Any other crops and infrastructure that could be observed en route were also captured. A specialist from the industry was organised to assist with the aerial identification of tobacco to ensure that nothing that has already been harvested was missed. A very knowledgeable dairy producer from Wilderness who is involved with many study groups were identified by the Outeniqua Research Farm to assist with the aerial identification of Novel Planted Pastures. It was possible to identify the hops fields without the help of a specialist.

The summer survey was only focussed on areas where one would expect irrigation practices. This does not include the irrigation of horticulture and viticulture crops as these crops are perennial and are therefore not seasonally bound in terms of crop identification. 4240 points were captured during this survey.

The following tracks were flown for the summer aerial survey:



Figure 24: Tracks flown for the summer aerial survey



The following map is indicating the location of the summer crops found during the aerial survey:

Figure 25: Summer crops captured during summer survey

For both Summer and Winter surveys cross quality control was implemented where one observer checked the data captured by another observer. In cases where conflict existed these were resolved, and re-training implemented where necessary. Below is a picture of such a cross control check.



Figure: 26 Crop captured by different observers and compared

2.9.3 Winter Crop Survey

The PICES winter aerial survey took place from 14 - 24 August 2023. During the survey the 2100 PICES points with an additional 300 points in areas where one would expect to find our crops of interest (small grain crops) were overflown as well as an additional 27 173 points captured en route. It was possible to capture this large number of observations (29 573 in total) due to the fact that two observers were on board the helicopter as opposed to the usual one observer in the helicopter. The 29 573 observation points are a combination of all types of crops as well as being captured as dryland or irrigated crops. This would help tremendously as ground truthing points for the remote sensing / artificial intelligence / machine learning processes.



Figure 27: Aerial survey team

The surveyors, using the software as described in a paragraph above, accompanied the pilot and captured crops and other attributes for all the pre-selected fields as well as all the additional fields that were overflown in the province. During the 2017/2018 survey a total of 269 744 fields were captured (a census approach) whereas during this survey a total of 29 573 fields were captured.

Below is a photo of the type of aircraft used in this survey.



Figure 28: Aircraft used during the survey

Below is a map of the crop categories captured during the winter aerial survey (including the pilot project).



Figure 29: Crop categories captured with the winter aerial survey

2.9.4 Processing of the Captured Data and Quality Assurance

The data was processed in batches per crop type after the areas were flown and detail investigations done where discrepancies were encountered between the office and field categories. The additional orchard, viticulture, vegetable, herb and flower data that was captured assisted immensely in updating groups of similar fields. As these fields were updated additional quality assurance was performed in the area checking for incorrect digitising, missed splits and incorrectly categorised fields.

2.10 Vehicle-Based Survey

2.10.1 General

The vehicle-based survey started on 9 September up to 9 November 2023 with four surveyors in the field and +-16 700 points verified with the survey. A second vehicle survey was conducted from the period 23 – 26 January 2024 for +- 700 unknown crops that were identified for a revisit after the quality assurance checks were completed. The following types of fields were extracted to be surveyed with the vehicle survey:

• All viticulture where it was not possible to distinguish between wine and table grapes.

- All the potential vegetable fields identified where it was not possible to obtain correct contact details with the previous census as well as new areas planted with vegetables to obtain producer contact details for the vegetable telephonic survey.
- All the orchards that could not be categorised.
- All shade-netting and tunnels where the crops could not be categorised.
- The locations of the Department's research farms were flagged for a field visit.

Below is a spatial picture of all the points surveyed by the vehicle-based survey teams.



Figure 30: Fields that were verified with the vehicle survey

2.10.2 Cooperation of Producers, Access and Security

In general, the feedback from the producers in the field was positive. There was, however, a couple of refusals and difficult producers, especially in the Robertson Valley and Ashton areas. Many of the producers were not aware of the survey even though the necessary protocol of communication through Agri Western Cape was followed.

The flood damage made it difficult to gain access to some properties and long detours had to be taken.



Damage observed with the floods and heavy rains

Figure 31: Damage observed with the floods and heavy rains

Safety is an ever-increasing concern. Numerous farmers reported theft. Some vegetable farmers are stopping production due to high costs of fencing and security. With the high unemployment rate people are stealing food directly from the fields, requiring more security and constant alertness

Comparing the 2012/2013, 2017/2018 and current census many changes could be observed with difficulty accessing some farms due to locked gates. A lot more cameras were installed at the main gates and more fencing and gates installed at farms. This include electric motorised gates with no keypad or intercom to be able to reach someone. Without a telephone number, some farms are inaccessible. A lot more farmers also now have large dogs on the premises. The issue with large farms or multiple pieces of land, is that it is now more gated at both ends, restricting movement and one can no longer drive through certain farms freely having to take long detours. A lot more locked gates were found especially in the Klein Karoo areas. The less populated and more rural areas had less security and access problems.

2.10.3 Processing of the Captured Data and Quality Assurance

As the field data was received, Quality Assurance was being performed and feedback given to the surveyors. The first two weeks' data was processed looking at the individual points captured to

ensure that the surveyors captured the data correctly. After that it was processed in batches per crop type and detail investigations done where discrepancies were encountered between the office and field categories. When the detail investigations were being performed the surrounding areas were also checked that served as additional quality assurance checks.

2.11 Telephonic Surveys

2.11.1 General Area Wide Surveys

The purpose of the survey was to obtain information about production and commodity trends and shifts per local municipality. Knowledgeable stakeholders that were contacted during the previous census survey were contacted again as well as new stakeholders provided by WCDoA, OABS and stakeholders met during the vehicle survey. The inputs of the surveys were utilised by OABS for their report and benchmark information used to compare areas planted per crop type.

2.11.2 Vegetable Surveys

The vegetable telephonic survey started mid November 2023 and was completed in the first week of February 2024. +- 606 producers were on the contact list which included producers that were willing to participate during the 2017/2018 survey. Producers who refused during the 2017/2018 were not contacted again. The telephonic survey was quite a challenge and some of the main challenges experienced are as follows:

- many producers did not answer an unknown number
- due to loadshedding or poor signal calls often did not go through even after several attempts
- producers agreed to participate but then ignored calls made at a more convenient time for them or ignored emails they requested to be sent with the questionnaire
- refused to participate

There were quite a few vegetable producers (especially in the Karoo area planting seed onions) where it was not possible to obtain contact numbers as it was not possible to gain access to their properties.

The following is a summary of the surveys conducted:

Type of Interview	No of Producers	% of Total
Successful interview	353	58%
Farmer does not farm with vegetables anymore or commercially	82	14%
Producer could not be reached	118	19%
Refusal	53	9%
Total	606	100%

Table 13: Types of telephonic surveys conducted

2.12 Remote Sensing / Artificial Intelligence / Machine Learning Processes

2.12.1 Objectives Of Winter Crop Mapping

The overall objectives of the winter crop mapping for the Western Cape Province are to:

- Identify different types of winter croplands i.e. barley, canola, fallow, lucerne/medics, winter wheat, and oats.
- Evaluate the temporal accuracy of using Sentinel-2 optical imagery for mapping different winter crops.
- Establish the best performing machine learning crop classification method for mapping winter crops.

2.12.2 Study Area

The study region is the Western Cape Province, South Africa. This area is known for producing various winter crops. The rectangular extent of this area is the latitudes -30.430° S to -34.834° S and longitude 17.757° E to 24.222° E. The province stands out as a prominent agricultural region for South Africa. The distribution of land in the Western Cape is largely known for vineyards, citrus, deciduous fruit, and crops. The agriculture in the region is also dependent on the rainy season which is mainly in the winter months from June to August, which makes the Western Cape ideal for planting of winter crops. The region has a wide range of landscapes, from coastal areas to mountainous terrain. Towards the upper regions of the province there is less agriculture as these areas are arid and generally unsuited to cropping.



Figure 32: Overview study area map for the Western Cape with 2023 ground control points used

2.12.3 Sentinel-2 Dataset

The Sentinel-2 Level-1C (L1C) data were acquired from the European Space Agency (ESA) Copernicus mission. These datasets are a multi-spectral satellite product with high spatial and spectral resolution. These instruments have 13 spectral bands (Table 14), including red, green, blue, near-infrared, red-edge, and shortwave infrared bands. The spatial resolution of these bands is shown in the Table 14. Only 7 of the 13 spectral bands available for Sentinel-2 were selected for this study. All the 20-meter resolution bands were resampled to 10-meter resolution using the nearest neighbour method.

Name	Description	Resolution	Central Wavelength
B02	Blue	10 meters	496.6nm
B03	Green	10 meters	560nm
B04	Red	10 meters	664.5nm
B05	Red Edge 1	20 meters	703.9nm
B06	Red Edge 2	20 meters	740.2nm
B07	Red Edge 3	20 meters	782.5nm
B08	Near Infrared	10 meters	835.1nm
B11	Shortwave Infrared 1	20 meters	1613.7nm
B12	Shortwave Infrared 2	20 meters	2202.4nm

Fable 14: Sentinel-2 satellite	product description	for selected spectra	l bands
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2.12.4 Overview of Methodology

The methodology flow chart shown in Figure 35 is the approach used in phase 2 of the study for mapping winter crops in the Western Cape. The methodology consists of the following: data collection and preprocessing of satellite imagery; spectral image enhancement by creating monthly means and computation of vegetation indices; model development and hyperparameter tuning; crop type prediction is enabled using the machine learning models and training data; testing or validation for accuracy assessment using testing data; model prediction and then the creation of the final winter crop map.



Figure 33: Overview of the methodology followed in this study

2.12.4.1 Data Collection

Agricultural field data were obtained from the 2023 winter survey for the Western Cape surveyed by SiQ. These field boundaries were used to extract sample points. From the available point data, a maximum of 2500 sampling points per class were randomly selected. This resulted in some classes having fewer sampling points for training and validation. Crop type classes were chosen based on the field classification. Some classes were grouped together; Fallow, Weeds and Stubble were grouped into one class, Fallow. The crop types and number of samples per class for the Western Cape Province are depicted in Table 15.

	Сгор Туре	Sample Field Data
1	Barley	1226
2	Canola	2403
3	Fallow	3824
4	Lucerne/Medics	2866
5	Oats	1828
6	Planted Pastures	1105
7	Wheat	2330

2.12.4.2 Input Feature Dataset

The heterogeneous landscape of the Western Cape makes distinguishing features on the surface difficult. Also, the spectral similarity of crop types is often an issue and therefore extracting other feature spaces from the Sentinel-2 spectral bands is necessary. Table 16 lists various vegetation indices derived from the multispectral datasets. These VIs along with the spectral bands described in Table 14 were used as input features for the models. Table 17 indicates all the image dates acquired to create the mean images used in this study.

Vegetation Indices	Abbreviation	Formula	References
Anthocyanin Content	ACI	$NID \times (D + G)$	Modified from Steele et
Index		$M/X \times (X + 0)$	al. (2009)
Atmospheric Resistant	ABVI	$NIR - (2 \times R) + B$	Kaufman and Tanre
Vegetation Index		$\overline{NIR} + (2 \times R) + B$	(1992)
Ashburn vegetation	AV1	(NIP = (1 - P) = (NIP - P))	Ashburn (1979)
index		(MK * (1 - K) * (MK - K))	
Chlorophyll Index Red-	CLRE	NIR	Gitelson et al. (2005)
edge	GERE	RedEdge1 - 1	
Enhanced Vegetation	EVI	2.5 × NIR - R	Huete et al. (1999)
Index	2.11	(NIR + 6R - 7.5B + 1)	
Excess Green Index	EXG	$2 \times \frac{G - R - B}{R + G + B}$	Woebbecke et al. (1995)
Green Normalized	GNDVI		Gitelson and Merzlyak
Difference Vegetation		$\frac{NIR - G}{NIR + G}$	(1998)
Index		MIX + 0	
Modified Soil-Adjusted	MSI	NIR - SWIR	Modified from Huete
Vegetation Index		$(NIR + SWIR + 0.5) \times (1.0 + 0.5)$	(1988)
Modified Simple Ratio	MSR	(NIR/R) - 1	Chen (1996)
		$(NIR/R)^{2} + 1$	
Normalized Difference	NDVI	NIR - R	Tucker (1979), Rouse et
Vegetation Index		NIR + R	al. (1974)

Table 16: Description of vegetation indices derived from Sentinel-2 satellite spectral bands

Normalized Difference Vegetation Index <u>RedEdge</u>	NDVIre	NIR - RedEdge1 NIR + RedEdge1	Barnes et al. (2000)
Normalized Difference Water Index	NDWI	$\frac{G - NIR}{G + NIR}$	McFeeters (1996)
Normalized Difference Yellowness Index	NDYI	$rac{G-B}{G+B}$	Sulik and Long (2016)
Red-edge Normalized Difference Vegetation Index	RENDVI	RedEdge2 - RedEdge1 RedEdge2 + RedEdge1	Sims and Gamon (2002)
Red-edge Re- normalized Difference Vegetation index	RERDVI	$\frac{NIR - RedEdge1}{\sqrt{NIR + RedEdge1}}$	Cao et al. (2013)
Red-edge ratio vegetation index	RERVI	$\frac{NIR}{RedEdge1}$	Cao et al. (2013)
Soil Adjusted Vegetation Index	SAVI	$\frac{(1+0.5) \times (NIR - R)}{NIR + R + 0.5}$	Huete (1988)
Triangular Vegetation Index	TVI	$\frac{[120(RedEdge2 - G) - 200 * (R - G)]}{2}$	Broge and Leblanc (2001)

April	May	June	July	August	September	October	November
2023	2023	2023	2023	2023	2023	2023	2023
20230402	20230502	20230604	20230701	20230801	20230902	20231001	20231101
20230404	20230503	20230606	20230702	20230802	20230904	20231002	20231103
20230405	20230504	20230611	20230703	20230803	20230906	20231004	20231105
20230407	20230505	20230613	20230704	20230805	20230907	20231005	20231108
20230410	20230507	20230616	20230708	20230806	20230909	20231006	20231109
20230413	20230508	20230617	20230711	20230807	20230910	20231009	20231110
20230414	20230509	20230618	20230712	20230808	20230912	20231010	20231111
20230415	20230510	20230622	20230713	20230810	20230914	20231011	20231112
20230417	20230512	20230623	20230716	20230811	20230916	20231012	20231113
20230418	20230513	20230624	20230717	20230812	20230917	20231014	20231114
	20230515	20230628	20230718	20230813	20230919	20231015	20231115
	20230517	20230629	20230719	20230815	20230920	20231017	20231116
	20230518		20230721	20230816	20230921	20231019	20231118
	20230519		20230723	20230817	20230922	20231020	20231119
	20230520		20230724	20230818	20230927	20231022	20231123
	20230522		20230727	20230820	20230929	20231024	20231124
	20230524		20230728	20230822		20231025	20231126
	20230525		20230731	20230823		20231026	
	20230527			20230825		20231027	
	20230528			20230827		20231029	
				20230828		20231030	
				20230830		20231031	

Table 17: List of Sentinel-2 image dates used in this study for phase 3 of the project

2.12.4.3 Classification Process

Random Forest

The Random Forest classifier is the most well-known ensemble learning algorithm (Breiman, 2001) that is widely used in crop classification studies. This approach uses an ensemble of decision trees that is trained, using bagging and feature randomization, to reduce overfitting and ensure a diverse tree structure. To predict the classification of various target classes, the RF algorithm groups individual trees using a majority vote for the final output. Enhancing the performance of the classifier is essential in producing high accuracy outputs. The GridSearch technique is used to fine-tune hyperparameters for the classification. The n_estimators parameter is used to

determine the number of decision trees to be used in the ensemble, while max_depth identifies the maximum depth of each tree, and max_features consider the number of features considered for splitting at each node. For this study, we used the scikit-learn Python library (Pedregosa et al., 2011) called RandomForestClassifier for modelling the crop types.

CatBoost Classifier

A gradient boosting algorithm, CatBoost, is an ideal method for handling of categorical variables such as crop type mapping. This classifier is especially useful in identifying patterns in heterogeneous datasets, such as in our study area, where complex agricultural fields are planted. The model creates weak learners which are simple decision-making trees, each tree is unique in the features and data points that is used for predictions. The weak learners are then used to create an ensemble that can produce high accuracy predictions. This is done using Boosting in the CatBoost model to continuously learn and correct any mistakes that are made to form the ensemble. Weighted voting is later used to determine the best predictions from the decision trees (Prokhorenkova et al., 2018). The GridSearch method was used for hyperparameter tuning, to maximise the accuracy of the classification model. These parameters included the optimal iterations, depth, and learning-rate.

LGBM Classifier

The LightGBM classifier is an efficient gradient boosting algorithm (Ke et al., 2017) which is a known ensemble learning method. This means that a combination of decision trees is created to form a strong predictive model. This method creates decision trees more efficiently and in a wiser depth, the leaf nodes are selected at each step where the highest information gain is possible. Using this approach ensures faster splits that improves performance with less nodes. This method is popular for its ability to produce results with less computational requirements such as RAM and improved predictions. In hyperparameter tuning the GridSearch method was employed to the following: number of boosting iterations or the total number of trees within the ensemble (n_estimators), the maximum depth of the trees (max_depth), and the learning rate that controls the step size of each iteration (learning_rate).

2.12.4.4 Experimental Design

The study identified four experiments (Table 18) to determine the best approach for winter crop classification. The aim for phase 2 of the project was to produce a working methodology for accurately mapping the winter crop types. Experiment 1 and 2 were developed using the April to November 2023 data, and these experiments only used the vegetation indices described in Table 3 as input features. Experiment 3 and 4 used data collected from April to November 2017 and followed the methodology described on the website (https://github.com/DariusTheGeek/Radiant-Earth-Spot-the-Crop-Challenge). For the purpose of this study, the Pytorch and ensemble learning was omitted, and experiment 3 and 4 used machine learning techniques (CatBoost and LGBM algorithms) from the Radiant Earth Spot the Crop challenge, that aligned well for the purpose of winter wheat classification.

	Period	Experiment Description
Experiment 1	2023_04 to 2023_11	RF + VIs
Experiment 2	2023_04 to 2023_11	CatBoost + VIs
Experiment 3	2023_04 to 2023_11	Radiant Earth CatBoost
Experiment 4	2023_04 to 2023_11	Radiant Earth LGBM

Table 18: Experimental Design for four experiments conducted in this study

2.12.4.5 Model evaluation

Accuracy assessment and cross-validation are essential to evaluating the performance of crop type classification models. The evaluation of these models helps to determine the reliability and accuracy of the classification outcomes. In this section, the methodology for model analysis is described.

Accuracy Assessment

The performance of the winter crop classification is determined using the accuracy assessment, which aims to correctly measure the classified classes of the crop types. The model predictions are evaluated by comparing them with ground truth data. Training samples are used to acquire the prediction of each class and then the testing data is used for accuracy assessment. The confusion matrix is compiled to provide the predicted class labels against the actual class labels. From the confusion matrix the following metrics can be acquired, including overall accuracy, precision, recall, and F1-score.

- A. Overall Accuracy: Is the proportion of correctly classified samples compared to the total samples in the dataset.
- B. Precision: The probability of classifying a specific class correctly within all the samples of that class.
- C. Recall: The probability of a sample classified as a class type is correctly identified
- D. F1-Score: The harmonic means of precision and recall.
- E. Support: these values are the number of instances in each class in your dataset, this provides context on the accuracy metrics discussed from A to D. This gives insight into the distribution of data across the different classes.

Cross-validation

The performance of crop classification models are assessed more efficiently when cross-validation techniques are used (Upadhyay et al., 2022, Reedha et al., 2022). This method is more useful to ensure overfitting is avoided during modelling. This method takes multiple subsets of data to train the model and the other remaining subsets is used for testing. Repeating this process multiple instances for assessment of the models is needed, and the performance metrics are then averaged to obtain more reliable estimates of the model's accuracy. In this study the 10 k-fold cross-validation approach was used. The accuracy assessment metrics can also be calculated in each fold, which gives a better representation of the model performance and variance.

2.12.5 Results Of Phase 2 Winter Crop Classification

2.12.5.1 Mapping Winter Cropping System with Machine Learning

For this study area, images were obtained from April to November, and the vegetation indices discussed in Table 19 were calculated. The winter crops flower between July and September, and these are expected to be the months where winter crops can easily be identified. Four experiments were created to identify the best performance of the machine learning algorithms to map winter crops in the Western Cape Province. The overall accuracy of these experiments is shown in Table 19. The highest overall accuracy was observed for experiment 2 (80.31%) and experiment 3 (81.09%), these two experiments also produced the highest kappa statistics of 0.76 and 0.77, respectively. Experiment 1 produced the lowest overall accuracy (75.81%) and kappa statistic (0.71). The results shown here indicates that the CatBoost algorithm is producing better accuracy models than the other machine learning algorithms.

Table 19: The overall accuracy and kappa coefficients for the four experiments using Julyto September imagery

Experiment	Experiment Description	Image Dates	Overall Accuracy (%)	Карра
1	RF	2023/04-2023/11	75.81	0.71
2	CatBoost	2023/04-2023/11	80.32	0.76
3	Radiant Earth CatBoost	2023/04-2023/11	81.09	0.77
4	Radiant Earth LGBM	2023/04-2023/11	79.18	0.75

Results from the cross-validation were obtained to further emphasize the accuracy of the models showed in figure 36. Experiment 4 showed the highest cross-validation accuracy scores, with the median value above 0.825, indicating that the model accurately trained the training samples. The box and whiskers plot for experiment 2 and 3 show that their accuracies are consistently indicating similar accuracies with median scores close to 0.82. These findings give high confidence in the accuracy of experiment 2, 3, and 4. Unfortunately, experiment 1 produced less favourable cross-validation accuracy scores with scores below 0.77. The median for experiment 1 was also indicated as below 0.76. These findings indicate that the models performed overall favourably for experiment 2, 3 and 4, whereas the model created in experiment 1 performed less favourably.



Figure 34: The cross-validation accuracy scores for the four experiments. The boxplots are the lower and upper quartiles (whiskers in black) and the black line in the boxplot is the median. The diamonds represent outliers in the data outputs, which are data points outside the lower and upper quartiles.

The confusion matrix for the classifications experiments 1-4 (Table 20, 21, 22, 23) was calculated for producing per class precision (producer's) and recall (user's), F1-Score and support metrics. Figure 37 represents these accuracies for experiment 1, 2, 3, and 4 across six different classes (Barley, Canola, Fallow, Lucerne/Medics, Planted Pastures, Oats, and Wheat). From these plots it is evident that the models have varying levels of performance across different crop classes. Among the experiments, Experiment 2 (CatBoost), experiment 3 (Radiant Earth CatBoost) and experiment 4 (Radiant Earth LGBM) consistently achieves high precision, recall and F1-scores across most classes. While experiment 1 (Random Forest) produced the lowest classification metrics throughout all the classes. In terms of performance per class, Planted Pastures represents the lowest-performing classes across all models. Canola is the highest performing class, with all four experiments consistently delivering the best metrics of precision, recall and F1-Score for this class.

	Barley	Canola	Fallow	Lucerne/ medics	Oats	Planted Pastures	Wheat	User's Accuracy
Barley	143	14	24	14	10	0	22	63.0
Canola	6	439	8	14	15	0	12	88.9
Fallow	1	4	651	56	11	13	4	88.0
Lucerne/ medics	2	9	95	466	26	14	8	75.2
Oats	14	15	34	44	204	7	72	52.3
Planted Pastures	0	7	37	54	20	94	5	43.3
Wheat	10	5	22	12	21	0	388	84.7
Producer's Accuracy	81.3	89.0	74.7	70.6	66.4	73.4	75.9	OA = 75.81

Table 20: Confusion Matrix for Experiment 1

Table 21: Confusion Matrix for Experiment 2

	Barley	Canola	Fallow	Lucerne/ medics	Oats	Planted Pastures	Wheat	User's Accuracy
Barley	205	4	8	6	15	0	9	83.0
Canola	3	446	7	10	10	1	9	91.8
Fallow	1	2	685	61	9	11	0	89.1
Lucerne/ Medics	5	0	66	465	20	16	9	80.0
Wheat	19	4	28	40	219	10	50	59.2
Oats	2	1	31	60	27	99	3	44.4
Planted Pastures	9	3	13	7	30	0	408	86.8
Producer's Accuracy	84.0	97.0	81.7	71.6	66.4	72.3	83.6	OA = 80.32

Table 22: Confusion Matrix for Experiment 3

	Barley	Canola	Fallow	Lucerne/m edics	Oats	Planted Pastures	Wheat	User's Accuracy
Barley	204	4	10	7	14	1	7	82.6
Canola	5	447	6	10	6	3	9	92.0
Fallow	1	0	692	54	9	13	0	90.0
Lucerne/ Medics	3	1	63	466	20	18	10	80.2
Wheat	18	2	27	39	222	12	50	60.0
Oats	2	1	27	54	24	113	2	50.7
Planted Pastures	10	5	11	4	33	0	407	86.6
Producer's Accuracy	84.0	97.2	82.8	73.5	67.7	70.6	83.9	OA = 81.09

Table 23: Confusion Matrix for Experiment 4

	Barley	Canola	Fallow	Lucerne/m edics	Oats	Planted Pastures	Wheat	User's Accuracy
Barley	192	5	11	9	17	0	13	77.7
Canola	4	442	7	14	8	5	6	90.9
Fallow	0	0	675	71	7	15	1	87.8
Lucerne/ Medics	5	1	73	458	23	12	9	78.8
Wheat	20	3	37	37	219	8	46	59.2
Oats	1	1	25	72	26	97	1	43.5
Planted Pastures	8	4	11	5	34	0	408	86.8
Producer's Accuracy	81.3	89.0	74.7	70.6	66.4	73.4	75.9	OA = 79.18



Figure 35: The bar graphs for per-class precision, recall, F1-score and support metrics for each of the experiments/classifications

2.12.5.2 McNemar's Test of Statistical significance

Table 24 presents the results of the McNemar's test for comparing the performance of the different experiments. This is a statistical test used to calculate the significant difference between two paired models based on the confusion matrices determined during crop classification.

Comparing experiment 3 results to the other three models showed no statistically significant differences in the performances of the models. The p-values exceeded the significance level of 0.05 in all three comparisons to experiment 3. This indicates that there is no strong evidence to suggest that one experiment performed significantly better than the other. The Z-values also consistently reflect minimal difference in performance between the models. These findings suggest that, within the context of the data and evaluation metrics, the models exhibit similar performance, and there is no clear advantage to choose one model over another.

	Table 2	4: McNemar's	Test Results for	r Model	Comparisons
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	Z-value	p-value
Experiment 1 vs Experiment 3	0.3162	0.7518
Experiment 2 vs Experiment 3	0.0000	1
Experiment 4 vs Experiment 3	0.3536	0.7237

2.12.5.3 Assessing the Spatial Patterns of Crop Types and Field Mapping for Winter Crop using Machine Learning

The crop type map representing the Western Cape Province was created using the model from experiment 2 (CatBoost). The winter crop map indicates that wheat is the dominant crop class in the western central region of the province (Figure 38A). Towards the Southern to Southeastern regions of the province where a large section of cropland is located, a more diverse variety of

crop types were mapped (Figure 38B). The results revealed that fields are generally mapped homogeneously within each field boundary, with few field boundaries containing more than one crop type, although this is not always the case. Mixing also known as pixel mixing occurs throughout for different reasons, such as along the field edge/boundary and where features or crop types have similar spectral signatures. There are also environmental factors and crop health that can influence field homogeneity causing inconsistencies in the field.



Figure 36: Winter crop type distribution from experiment 2 for the Western Cape

2.12.5.4 Area Estimates

Figure 39 presents a comparative analysis of the estimated areas for the different crop classes along with their corresponding 90% confidence intervals. This was calculated using the method standardised by Olofsson et al. (2013) to use the confusion matrix to adjust the area error for each class. The graphs indicate variations in crop areas across four experiments for each class. Notably, canola and fallow classes exhibits the most significant fluctuations in estimated area, especially evident in experiment 1, where the area estimates are much higher than in other experiments. Across all the crop classes, the area estimates differ very little between experiment 2 and experiment 3. This was expected as these models performed very similar when the accuracy assessment was calculated. The inclusion of confidence intervals as whiskers on each bar provides insight into the precision of the estimates, emphasizing the reliability of the reported values.



Figure 37: Variability in estimated crop areas across different experiments, along with corresponding confidence intervals, highlighting the precision and reliability of the reported values

Table 25 presents the user's and producer's accuracies per class for each of the four experiments conducted. The user's accuracy (UA) represents the probability that a pixel classified as a certain class is correct, while the producer's accuracy (PA) measures the probability that a pixel belonging to a certain class is correctly classified. Across experiments, canola consistently demonstrates high accuracies, indicating robust classification performance. Conversely, oats and planted pastures exhibit comparatively lower accuracies across experiments, suggesting challenges in distinguishing these classes. The inclusion of error-adjusted 90% confidence intervals for both UA and PA offer valuable insights into the reliability of the accuracy estimates, enhancing the interpretation of classification results. These results tie in with section 3.1 where the confusion matrices were discussed.

Experiment 1								
Winter Crop Class Name	UA	PA	90% Confidence Interval UA	90% Confidence Interval PA				
Barley	63.00	81.25	63.00	74.97				
Canola	88.87	89.05	88.87	83.62				
Fallow	87.97	74.74	87.97	84.48				
Lucerne/medics	75.16	70.61	75.16	76.70				
Oats	52.31	66.45	52.31	64.80				
Planted Pastures	43.32	73.44	43.32	33.97				
Wheat	84.72	75.93	84.72	81.66				
			Error-Adjusted OA	78.75%				

Table 25: The user's and producer's accuracies (%) per class for each experiment, along with the
error-adjusted 90% confidence interval accuracies

Experiment 2				
Winter Crop Class Name	UA	ΡΑ	90% Confidence Interval UA	90% Confidence Interval PA
Barley	83.00	84.02	83.00	81.14
Canola	91.77	96.96	91.77	94.18
Fallow	89.08	81.74	89.08	88.19
Lucerne/medics	80.03	71.65	80.03	77.52
Oats	59.19	66.36	59.19	64.62
Planted Pastures	44.39	72.26	44.39	38.18
Wheat	86.81	83.61	86.81	89.15
			Error-Adjusted OA	81.48%
Experiment 3				
Winter Crop Class Name	UA	ΡΑ	90% Confidence Interval UA	90% Confidence Interval PA
Barley	82.59	83.95	82.59	81.36
Canola	91.98	97.17	91.98	94.42
Fallow	89.99	82.78	89.99	88.85
Lucerne/medics	80.21	73.50	80.21	79.32
Oats	60.00	67.68	60.00	64.51
Planted Pastures	50.67	70.63	50.67	37.29
Wheat	86.60	83.92	86.60	89.46
			Error-Adjusted OA	82.08%
Experiment 4				
Winter Crop Class Name	UA	РА	90% Confidence Interval UA	90% Confidence Interval PA
Barley	77.73	83.48	77.73	79.52
Canola	90.95	96.93	90.95	94.23
Fallow	87.78	80.45	87.78	87.02
Lucerne/medics	78.83	68.77	78.83	75.98
Oats	59.19	65.57	59.19	63.37
Planted Pastures	43.50	70.80	43.50	34.32
Wheat	86.81	84.30	86.81	89.51
			Error-Adjusted OA	80.12%

2.12.6 Conclusions

The findings of this phase suggest that the CatBoost machine learning methods produce the highest accuracy results, above 81% overall accuracy for experiment 3. The results of experiment 4 showed only a 2% difference in accuracy compared to experiment 3, and 1% difference from experiment 2, with the results from experiment 1 (RF) showing lowest classification accuracy, with a 5% difference in overall accuracy compared to experiment 3.

The statistical significance McNemar's Test showed the results of these experiments produced no significant statistical difference between the performance of the models. This indicates that, based on this test, no specific experiment can be identified as being significantly improved in accuracy over another. However, based on the overall accuracies of the models, the model in experiment 3 can be chosen as the final classification for winter crops in 2023.

While experiment 3 is chosen as the final classification, it is noteworthy that the other experiments (experiment 2 and experiment 4) also demonstrate success in accurately mapping the winter crops for 2023.

The following classes were successfully identified: barley, canola, fallow, lucerne/medics, planted pastures, wheat, and oats. The most confusion were found in the planted pastures class. This is generally caused by the concept of pixel mixing, which is found when some confusion takes place between different classes, primarily where spectral signatures are similar for two or more classes. This could also be due to the smaller number of available ground truth data points.

2.13 Processing of the Remote Sensing / Artificial Intelligence / Machine Learning Data

The aim of the desktop crop categorisation process was to identify the crop types of as many as possible fields to be able to reduce the number of fields that could cause confusion with the deep learning methods. Fields that could possibly be classified as fallow/weeds with these methods were rather classified as, for example, cleared orchard, vineyard, or protea, abandoned orchard, possible vegetables, etc. The crop classes that had higher confidence scores with the deep learning categorisation processes were barley, canola, wheat, oats, lucerne/medics, planted pastures and fallow/weeds.

The deep learning models that produced the highest accuracy results, with above 80% overall accuracy, were the ones that used the CatBoost algorithm, as well as the combination of the Radiant Earth and CatBoost algorithms. These models produced results in raster format, with each pixel indicating the classified crop. To assign the classified crops to the corresponding fields, all crop types per pixel were summarised per field boundary and expressed as percentages – for both models. It is important to note that before this process, the field boundaries were evaluated on in-season Sentinel 2 imagery to add additional field splits where necessary. The purpose of this exercise was to increase accuracy when assigning crop classifications to the field boundaries.

Based on the crop percentage per field, the majority crop type was calculated for the field - for both models. When comparing the calculated majority crop for the two models on a field-by-field basis, it was found that there was a high level of correlation - approximately 93% - between the results of the two models. For the fields where the calculated majority crop differed between the models, the majority crop with the higher percentage was assigned to the field.

As part of the quality assurance process, zonal statistics were calculated for the different grain crops – barley, canola, wheat, lupines, and oats – using historical data. The purpose of these heatmaps was to identify areas with a higher likelihood of finding a specific crop, and by extension, areas in which the likelihood of finding a specific crop is low. These heatmaps were used to identify and correct possible incorrectly classified crops.

The classifications done with the abovementioned deep learning methods, did not include lupines. Therefore, it was necessary to do a separate process for the classification of lupines. The heatmap for lupines, as described above, was used to identify the main production area for lupines. For this area, a random forest classification method was used to find potential lupine fields, utilising Sentinel 2 imagery of August 2023. A visual inspection of these potential lupine fields was done to determine whether lupines are planted on the field, using the Sentinel 2 imagery as reference. The colour of the lupines on the Sentinel imagery can be distinguished from the other crops of interest, which made this process possible.

It was noticed that the accuracy of the crops classified with the deep learning methods was higher in the grain areas, with larger and more uniform fields. In areas with smaller fields, it was in some instances less accurate with these fields often classified as oats. The oats number is thus slightly higher than what it should be. Triticale was not categorised separately and could have been categorised under wheat, barley, or oats.

2.14 Quality Assurance

Quality Assurance was performed throughout all the process. Detailed Quality Assurance was performed with the initial digitising of the field crop boundaries and feedback given regularly to the team of digitisers. Then as the areas were scanned with the crop categorisation process any missed, or incorrectly digitised fields and splits were updated.

During the processing of the aerial and vehicle-based survey data as well as the field visit data received from WCDoA, detailed investigations were performed where discrepancies were encountered between the office and field data and corrections made as necessary. During this process missed and uncategorised fields were also identified. These fields were investigated to determine if it would be possible to determine the crop type in the office with Google Earth, Google Streetview, through the Internet or telephonically. +-700 fields were identified for a vehicle revisit in the field in January 2024. After the vehicle revisits there were +- 430 fields remaining with an unknown orchard / flower crop type of which most were far out with difficult or no access. These fields were investigated again and producers in the area contacted to see if it was not possible to determine the crop type. Many fields could be categorised, but there were however, fields where information was refused, or mails and messages not responded to. WCDoA and some stakeholders like Subtrop and chairmen from associations of smaller niche crops assisted with the location of new plantings and unknown crops.

3 BENCHMARK DATA AND COMPARISONS

3.1.1 Orchards, Viticulture, Grain, Oil Seeds and Grain

Benchmark figures were obtained from various stakeholders and statistical reports to be able to compare /verify the areas calculated with the industry statistics. In areas where there are big discrepancies, investigations were done to verify the categorised areas. Please find the comparison between the SiQ and benchmark figures with notes to explain the deviations.

Table 26: Comparison of calculated orchard areas with industry figures

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Almonds 1 963 2 200 -11% Producer 2023	Almonds	1 963	2 200	-11%	Producer	2023	
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Macadamia nuts 2 089 2 866 -27% SAMAC 2023 2866 ha figure overstated	Macadamia nuts	2 089	2 866	-27%	SAMAC	2023	2866 ha figure overstated

Table 27: Comparison of calculated berries, viticulture, grains, oil seeds, tobacco, hops and honeybush areas with industry figures

BERRIES	2023 Census figure (Ha)	Industry figure (Ha)	Deviation from Industry Figure (%)	Source	Year of Industry Figure	Notes
Blueberries	1 762	1 432	23%	Berries ZA	2023	SiQ investigated and cannot find incorrect areas, also not all producers are Berries ZA members like Saronsberries
Raspberries	126	119	6%	Berries ZA	2023	
Persimmons	327	210	56%	Charl Stander	2022	SiQ investigated and cannot find incorrect areas

VITICULTURE	2023 Census figure (Ha)	Industry figure (Ha)	Deviation from Industry Figure (%)	Source	Year of Industry Figure	Notes
Wine grapes	80 593	86 544	-7%	SAWIS	2022	
						SIQ figures includes dried
Table grapes	14 718	12 252	20%	SATGI	2022	grapes
Dried Grapes		2 218	- 100%	Raisin SA		
Total Table						
Grapes/Dried Grapes	14 718	14 470	2%			

	2023 Census figure	Industry figure	Deviation from Industry Figure		Year of Industry	
GRAIN AND OIL SEED	(Ha)	(Ha)	(%)	Source	Figure	Notes
Barley	109 858	107 600	2.1%	CEC	2023	
Canola	134 426	131 200	2.5%	CEC	2023	
Wheat	361 791	365 000	-0.9%	CEC	2023	
Lupines	17 023	16 000	6.4%	CEC	2023	
Oats	151 538	157 000	-3.5%	CEC	2023	The oats figure includes oats planted for feed etc
Maiza	6 175	2 750	64 70/	CEC	2022	The difference is due to maize planted for feed that is not included in CEC
Maize	61/5	3 /50	64.7%	LEC	2023	rigure

TOBACCO, HOPS &	2023 Census figure	Industry figure	Deviation from Industry Figure		Year of Industry	
HONEY BUSH	(Ha)	(Ha)	(%)	Source	Figure	Notes
Tobacco	176	250	-29.5%	Producer	2023	
Hops	466	403	15.7%	SAB Hops	2023	
Honey bush	245	200	22.3%	Researcher	2023	

3.1.2 Vegetables

Due to the fact that a full census of all the fields was not executed, it was relied on visual interpretation from imagery and the vegetables that were identified during the aerial and vehiclebased surveys for areas planted with vegetables. There is thus the possibility that some areas planted with vegetables were missed. Also, it is sometimes quite challenging to determine the extent of the areas planted under vegetables for a specific farming operations. To calculate the vegetable figures, the data captured during the telephonic vegetable survey was used and the vegetable areas with a crop captured outside the boundaries of these interviewed farming operations added to the figure to be able to add areas where producers refused to give information, or it was not possible to get hold of them. There are +- 934 ha where the vegetable crops could not be categorised due to producers refusing crop information or producers could not be contacted.

4 DATA LAYERS AND SUMMARY SPREADSHEETS

One of the primary deliverables for this project is the spatial data layers. What follows is a summary of these spatial layers. This also forms part of the final deliverable:

Final datasets	Туре	Comment
Fields dataset with winter crops	Polygon	See metadata
Fields dataset with summer crops	Polygon	See metadata
Detail Novel Planted Pasture Species identified	Polygon	See metadata
Shade-netting dataset with shade-net type	Polygon	See metadata
Tunnel boundaries	Polygon	See metadata
Livestock and Agro-processing infrastructure	Point	See metadata
Game farm boundaries	Polygon	See metadata
Vegetables – producer details	Polygon	See metadata
Year figures: Vegetables – Open ground	Polygon	See metadata
Year figures: Vegetables – Shade netting	Polygon	See metadata
Year figures: Vegetables – Tunnels	Polygon	See metadata
Year figures: Vegetables – Other	Polygon	See metadata

Table 28: Spatial dataset delivery

List of Excel spreadsheets and other data:

 Table 29: Excel spreadsheets and other data delivery

Document	Туре	Comment
Total Potential Production Value Per Crop	Excel	
General Area Survey Reports	Excel	
General Area Trends from Stakeholders and Producers	Pdf	
Summary Livestock and Agro-processing 2017 vs 2023	Excel	
Details Shade-netting and Tunnel summaries as on 31 January 2023	Excel	
Detailed Vegetable Areas planted	Excel	
Algorithms for Deep Learning Processes	Pdf	
Metadata	Word & Pdf	

5 REFERENCE PERIOD

It is important to note the reference period for the information that was obtained for the study. The applicable reference period for the production data is January 2023 – January 2024. In terms of production of crops our main aim was to determine the area planted for each crop during this reference period. For the field crops we have three information sets that were obtained:

- Winter crops that were planted during the winter of 2023
- Summer crops that were planted during the 2023 summer season.
- The area planted for each crop during the total reference period. Crops such as wheat are for example almost exclusively planted during the winter season and therefore the winter survey would have captured the bulk of the crop. Other crops, especially vegetable crops can have a winter crop, a summer crop and also more rotations throughout the reference period. It would therefore not be sufficient to only obtain a winter snapshot and a summer snapshot of the crop, but you would also require a total area planted throughout the reference period.

6 PICES EXPOSURE FOR MINISTER OF AGRICULTURE

SiQ was requested to provide an opportunity to the Minister of Agriculture in the Western Cape, Dr Ivan Meyer, for some exposure to the aerial observation that was utilised for the collection of field data. On 22 February 2024 a delegation from the Minister's office as well as officials from the Western Cape Department of Agriculture met the SiQ team at Cape Town International Airport. After a short introduction presented by the CEO of SiQ, Mr Eugene du Preez, summarising the project methodology and objectives, the delegation was taken to the helicopter. The SiQ Field Manager, Mr Carl Visagie (also a farmer), with more than 8000 hours of field observation experience was responsible for exposing the delegation to the actual field data collection process. Each of the delegates in the helicopter was given a tablet that was connected to the field capturing laptop that was operated by the Field Observer. This enabled the delegation to experience exactly how the field data was captured on the field capturing software.

The routing for the survey can be seen below in the highlighted pink line that are connected to the spatial points to be surveyed:



Figure 38: Screenshot of flight plan

After returning from the 1-hour flight a proper debriefing was held. The Minister indicated that he thoroughly enjoyed the flight and that he was really impressed with this methodology of collecting field data. He mentioned that he was surprised by how much could be identified from the air when flying at a low altitude. He was also really impressed by the knowledge of our Field Manager and his ability to distinguish the various crop types from the air. Below are some more pictures of the events of the day.



Figure 39: Photo opportunity with the Minister

7 RECOMMENDATIONS AND CONCLUSION

We would firstly like to thank the WCDoA for the opportunity to be involved in this project for the third time now (this is the third iteration of the baseline mapping). We strongly believe that this project will be duplicated in all the other provinces in the country and that it is just a matter of time. The importance of this information not just for agriculture but for several other Government

Departments, NGO's and private organisations has been proven repeatedly. This baseline information will hopefully be used in many applications within a number of industries and will most certainly lead to better planning, policy making and general decision making.

We would like to congratulate the WCDoA for their boldness in taking on a project of this nature that has not been rolled out at this scale anywhere else in the country. We have mentioned it before, but the Western Cape province is the only province that has done more than one iteration of the baseline mapping project. We have stated many times that the real value in this baseline information will only be realised when multiple iterations are done and therefore trends can be detected as well as the measurements of the impact of policies on the industry as a whole. The success of planning that was based on this baseline information can also now be properly measured. We firmly believe in the fact that you can only manage what you are able to measure. We can also state that our experience with the Western Cape Department of Agriculture has been extremely positive. We have found that the WCDoA is extremely professional and from an administrative point of view extremely efficient. We have found the administration to be very effective and we as a service provider to the WCDoA have been treated exceptionally in terms of the payment of invoices. This has removed a great deal of stress and management from our side and ensured that we could put all our attention on the execution of the project. We could manage our cash flow very accurately as we could rely on the payment dates to materialise as agreed upon.

The TOR for this project required remote sensing to be utilised and therefore the bulk of the aerial observations was replaced by remote sensing and the classification of crop types by means of satellite imagery. This statement would translate to the fact that whereas during the previous two iterations all farms in the province were overflown to capture information on all crops (every single potential field that could have been planted was overflown), livestock, agro-infrastructure (initial capturing and verification) as well as agri-tourism (initial capturing and verification). During this survey only statistical selected fields were overflown (as part of the Producer Independent Crop Estimates System) and data was captured for these fields (in terms of crops) and then as much as possible information was captured when routing from one statistical selected field to another. Ultimately this would translate in only approximately 10% of the fields that were overflown. This most certainly had an impact on the accuracy of the data that was captured for this project when compared to the previous iterations.

Whereas the aerial observations combined with vehicle-based surveys would translate to crop type identification accuracy of greater than 98%, remote sensing classification varies significantly in terms of accuracy (depending on the crop type) and is in the order of around 80%.

The fact that only around 10% of potential fields were overflown (therefore also not more than 10% of farms that were overflown) it would have the implication that very little data could be collected on livestock as well as game.

During the previous two iterations the aerial observation was also used extensively for the verification and validation of all the office mapped information such as agro-processing infrastructure. Furthermore, in some cases new agro-processing infrastructure was mapped that was not yet visible on the satellite imagery/ aerial photography that was used for the mapping. This was not possible during this iteration.

The requirement for the extensive use of remote sensing (as opposed to aerial observations census approach) was driven by budget constraints. Given the impact of COVID 19 and other
financial challenges recently these budget reductions are completely understandable. However, we would strongly recommend that for future iterations of the project it may be considered to alternate the implementation of a more remote sensing approach with the aerial observation census approach. Thus, for the next iteration we recommend that the aerial observation census approach be considered should the budget allow for it.

We wish the WCDoA the best of luck in their efforts to add additional value to the already existing valuable information. We would also like to assure them of our continuous support of the project.